3-4-2021

Manufacturing and Materials

University of Maine Artificial Intelligence Initiative

UMaine Artificial Intelligence: Manufacturing and Materials

Date: March 4, 2021
Run Time: 01:00:09
https://youtu.be/-i_U9O_nFeI

UMaine AI draws top talent and leverages a distinctive set of capabilities from the University of Maine and other collaborating institutions from across Maine and beyond, while it also recruits world-class talent from across the nation and the world. It is centered at the University of Maine, leveraging the university's strengths across disciplines, including computing and information sciences, engineering, health and life sciences, business, education, social sciences, and more.

Transcript is machine generated, unedited, in English.

00:03
okay
00:03
um welcome to the humane artificial
00:07
intelligence webinar
00:08
on ai for manufacturing my name is ali
00:12
abedi i'm associate vice president for
00:13
research at university of maine and i'm
00:16
excited to introduce our panel of expert
00:19
speakers from academia
00:22
industry and government agencies to talk
00:24
about
00:25
what's happening on artificial
00:27
intelligence use and manufacturing and
00:29
materials

00:30
so from wherever you're joining us
00:32
either from
00:33
the west coast or east coast of the
00:35
united states or from
00:38
europe in ieee india or i typically
00:42
china colleagues i welcome everybody
00:44
here
00:44
good morning good afternoon and good
00:46
night depending on
00:47
where in the world you're tuning in um
00:50
we are going to have
00:52
hsp here talk for almost 10 minutes
00:54
about
00:56
the topic of ai for manufacturing uh
00:59
feel free to
01:00
post your questions in the q a as they
01:03
come to your mind
01:04
and after all the first speakers are
01:06
talking uh talks are over then i will
01:09
um pose the questions and then we can go
01:12
over the question and
01:13
uh answer period toward the end of the
01:16
program so this is a one hour webinar it
01:18
will be recorded and

01:20
um we'll post it basically later on
01:23
so without further ado let me
01:27
start the panel by introducing our first
01:30
speaker dr tony schmitz is a professor
01:35
in mechanical aerospace and biomedical
01:37
engineering department at university of
01:39
tennessee in knoxville
01:40
with a joint faculty appointment at oak
01:43
ridge national laboratory he's a very
01:45
distinguished and accomplished
01:48
researchers if i want to read his bio
01:50
it will take the entire hour so let's
01:52
skipped that but i will just highlight
01:55
that
01:55
he is one of the experts in the country
01:57
in terms of uh manufacturing
01:59
and also uh he has received a number of
02:02
awards and recognitions like young
02:04
investigator award and
02:06
nsf career award has lots of patents and
02:09
publications so we are very
02:11
honored and excited to listen to dr
02:14
schmitz today so tony take it away
02:20
thank you like i can only go down from

02:22
there so let me let me try to do my best
02:25
um so my interest is in
02:29
trying to understand how we can leverage
02:32
advances in machine learning
02:34
for machining so machine learning for
02:37
machining
02:37
and in particular milling operations is
02:40
what i'm interested in
02:41
um so how can we kind of bridge this gap
02:44
between
02:46
the great work that's been done in
02:47
machine learning and the manufacturing
02:49
shop
02:50
floor so i'm going to describe today one
02:52
particular
02:54
implementation of machine learning and
02:57
i'm going to use
02:58
models that we've developed in the past
03:01
for machining
03:02
as a way to guide that machine learning
03:06
process
03:06
so this physics guided machine learning
03:08
approach says
03:10
i have some physics-based models i can

03:13
use those as a low-cost way to generate
03:16
a lot of data to initially train my
03:19
machine learning model
03:20
but because i have uncertainties
03:22
associated with that physics-based model
03:25
i can improve my machine learning model
03:27
now by collecting new data
03:29
and adding that to the original data set
03:32
that was provided by my physics-based
03:34
models
03:35
so i'm going to show that application
03:37
with relation to
03:39
milling so first i'll talk just a bit
03:42
about machine learning
03:44
and then the models that we apply the
03:45
physics-based models
03:47
and then i'll demonstrate briefly a case
03:49
study that we completed to demonstrate
03:51
this approach
03:53
so machine learning as we know is a
03:55
data-driven approach
03:57
we have machine learning and statistical
04:00
techniques which can both be applied
04:02
where i want to learn from my either

04:04
continuous sensor data or
04:06
discrete measurement results during or
04:08
after the manufacturing process
04:11
so this is this is a great advantage
04:14
when i don't have a great
04:16
an understanding of the relationship
04:18
between the inputs
04:20
and outputs for my manufacturing process
04:23
in that in that way i can develop those
04:26
correlations
04:27
simply from the data that i collect
04:29
during the process
04:30
the challenge is that those correlations
04:32
don't know about my physical laws and
04:34
sometimes they can lead me to
04:36
a place i didn't want to go because
04:39
either inadequate data or
04:40
uncertainty in my data and so on and it
04:43
may be difficult to generalize beyond
04:45
that training data set
04:47
so in this work we're leveraging machine
04:50
learning
04:50
in particular classification which is a
04:53
supervised learning approach

04:55
where i'm trying to collect data and
04:56
then make decisions based on that data
04:59
by classifying the outcomes for example
05:02
if i showed you a face image
05:06
you could tell me probably whether that
05:07
was a male or a female
05:11
in the same way what i want to do here
05:13
is i want to introduce
05:15
them you to a spindle speed and
05:18
with combination for my machining
05:20
parameters and then have you tell me
05:22
is that going to be stable or unstable
05:24
in other words am i going to get good
05:26
machining performance or poor machining
05:28
performance from that combination
05:30
there's lots of choices and we've
05:32
applied some of those the one i'll show
05:34
you today is a k-nearest neighbor
05:36
very simple approach okay so i said
05:38
we're going to have physics-based models
05:40
that we're going to use to train our
05:41
algorithm
05:42
so one of the things i need to know is
05:45
the vibration behavior

05:47
of this tool holder spindle machine
05:49
combination that i selected for this
05:52
machining activity
05:53
so we're going to use an approach where
05:55
we take models
05:57
of the holder and tool and then we
05:59
couple them
06:00
in the frequency domain to a measurement
06:02
of the spindle and
06:03
machine in order to predict those
06:06
assembly dynamics or what's the
06:07
vibration response
06:09
at the at the end of my cutting tool
06:12
where i'm going to be performing the
06:13
machining test
06:15
so there's lots of equations here but
06:17
essentially what this is saying
06:19
is if i can describe the dynamics of my
06:22
components of my individual pieces
06:25
then there's a there's an analytical way
06:27
to put those dynamics together
06:29
to predict the assembly dynamics and so
06:33
ultimately by following
06:36
um the the modeling of the individual

06:39
pieces
06:41
compatibility conditions at the boundary
06:43
and then equilibrium conditions where
06:44
i'm
06:45
connecting things i end up with an
06:47
equation which says i can predict the
06:49
assembly dynamics
06:51
from the component dynamics so that's
06:54
one of the models
06:58
so have you shown there that's a milling
07:00
cut for those of you who haven't spent a
07:02
lot of time around milling machines
07:04
so what you saw was a rotating tool
07:06
removing material
07:07
and flinging these chips away as it as
07:10
it cut away that material
07:12
so one of the things we need to
07:14
understand is that the tool is not
07:16
rigid and there's forces applied to that
07:18
tool
07:19
dynamic forces in order to fling away
07:21
those chips
07:23
and so that leads to a situation where i
07:25
have vibrations during my cutting

07:27
process
07:28
and those vibrations can be good we call
07:30
forced vibrations or there can be bad
07:32
what we call chatter or self-excited
07:34
vibrations
07:36
um so in terms of that modeling i have a
07:38
mechanistic approach to describe
07:40
those vibrations which includes cutting
07:42
force
07:43
that cutting force we estimated using
07:46
finite element
07:47
simulation to determine these
07:49
coefficients that relates the force to
07:51
the chip that i'm removing
07:54
okay so if i have my structural dynamics
07:56
that i predicted in my cutting force
07:58
model that i predicted i can bring those
08:00
together
08:01
into a frequency domain solution that
08:04
separates the bad vibrations
08:06
chatter from the good vibrations the
08:08
stable or forced vibrations and so the
08:10
gray
08:11
region in that plot is the is the bad

08:14
vibrations
08:15
and the white region is where we have um
08:18
good machining behavior okay so the big
08:21
thing that i
08:22
face when modeling mechanistically when
08:25
i use physics-based models to describe
08:27
this approach is
08:29
if i make a prediction and then perform
08:31
an experiment
08:32
and that experiment doesn't agree with
08:34
my prediction
08:35
i do not have a backwards solution i
08:38
only have the forwards
08:39
solution so that's what was very
08:41
intriguing to me about machine
08:43
learning is to enable me to connect
08:46
my experimental result to the inputs
08:50
in a way that wasn't available to me
08:52
before so here's a case study that we
08:54
ran
08:54
i said fine i'm going to start with the
08:57
models but i'm going to interject
08:59
errors into those models so they're
09:01
going to be not quite right

09:03
and then i'm going to compare the the
09:06
initially trained
09:07
model the machine learning model
09:10
to the true the true
09:13
behavior by adding points so i'll add
09:17
points to the original data set
09:19
one at a time until i converge
09:23
on that true solution okay so
09:26
using this k nearest neighbor approach i
09:29
trained it
09:30
from the original data that had errors
09:32
in it
09:34
and then now i have a mapping between
09:37
stable and unstable behavior in my model
09:40
so that's the gray zone there
09:42
the the blue curve is just saying that's
09:44
the true the true response that i don't
09:46
know yet
09:48
okay so now we start performing
09:50
experiments where
09:51
i update the points by tests
09:54
in this case at a five millimeter axial
09:57
depth of cut for the machining operation
09:59
so i update

10:01
in a smart way if i get a result i say
10:04
okay everything below that result
10:06
is stable if i get a positive or a
10:09
stable result
10:10
if i get an unstable result i say okay
10:13
everything above that result is unstable
10:15
so not only am i updating at the point
10:17
that i tested
10:18
but also surrounding points based on
10:20
what i know
10:21
as a machining dynamics person so then i
10:25
did it at different
10:26
axial depths and the k nearest neighbor
10:30
improves as i add these data points and
10:33
so you can see us walking through that
10:35
procedure and indeed
10:37
converging on the true behavior and so
10:40
this convergence criteria
10:41
i showed there's the number of correct
10:43
points relative to the number
10:45
of total points and so you can see that
10:47
that ratio improves
10:49
as we as we proceed with the testing
10:53
okay so i know that was quick but i just

10:55
wanted to give you a flavor
10:57
for how we can use models for
11:00
manufacturing
11:01
processes to see the machine learning
11:03
algorithm
11:04
and then update that algorithm with new
11:06
data so thank you and i'd welcome any
11:09
questions
11:11
thank you very much dr schmitz for the
11:14
great presentation
11:16
so now that we heard about the academic
11:18
side of
11:19
um manufacturing especially
11:22
talking about the physics based modeling
11:24
now we are going to the industry side
11:26
and our next next speaker um dr andrew
11:29
henderson will
11:31
um talk about the industry experience so
11:34
it's my great pleasure to
11:36
welcome dr andrew henderson to the
11:38
podium he's the cto
11:40
for primo incorporation he has over 15
11:43
years
11:44
of experience in advanced technology

11:46
data acquisition
11:48
data analysis and process and system
11:50
modeling and same as before
11:52
if i want to go over his accomplishments
11:55
he won't have his 10 minutes to talk
11:57
so i will stop here and welcome andrew
11:59
to the podium
12:01
thank you i i um i
12:04
should be sharing my screen now um let
12:07
me make it full screen
12:09
um so uh again thanks for thanks for
12:12
having me i
12:13
i i'm happy glad to be here i thought
12:16
maybe it'd be worthwhile to take just a
12:19
moment a brief moment in the beginning
12:20
to talk about who promo is
12:22
primo is a we have a product called
12:25
razer
12:25
that's uh an advanced analytics engine
12:29
that takes data from industrial
12:31
operations
12:32
and uh analyzes it to create these
12:35
notifications these things we call
12:36
insights

12:37
and those insights are are bits of
12:40
information that
12:42
operations people can go use to improve
12:44
productivity
12:45
and uh it accomplishes razer
12:47
accomplishes what it does
12:49
because we we leverage uh a bunch of
12:52
different techniques from the field of
12:54
artificial intelligence
12:55
and this of industry for industry is a
12:58
reflection of the fact that
13:00
uh all of our leaders come from industry
13:03
in some form manufacturing mining
13:05
and so we bring our experience to how
13:08
we develop razer and apply it in the
13:12
in industry and so i
13:15
i what i have is a few different
13:17
examples of how
13:19
uh andrew sorry to interrupt i think we
13:21
can't see your screen
13:22
so maybe you share it again please oh
13:25
did i
13:26
sorry i didn't do the final click i
13:29
apologize

13:31
can you see now yes perfect thank you so
13:35
um so so i have a few examples here
13:39
of of how uh various
13:43
uh assets or aspects of artificial
13:45
intelligence are applied
13:47
are applied to solve problems in
13:48
manufacturing
13:50
and uh there's an arc to the
13:52
presentation where i start out
13:53
i talk about consumer ai uh and then i
13:56
end up
13:57
talking about you know some of the
13:59
challenges that real world
14:00
in manufacturing faces and how we might
14:03
deal with them
14:04
so the first example here this is around
14:06
product quality this is
14:08
as as dr schmitz mentioned a moment ago
14:12
taking images and recognizing cats or
14:15
features or faces in the images being
14:18
able to classify
14:19
what's in them and so we can take those
14:21
exact same
14:23
approaches and from consumer ai

14:27
and more or less directly apply them to
14:30
manufacturing where
14:31
if you have an inspection station that's
14:34
that with a
14:34
with a camera that's taking images of a
14:36
product then you can feed those images
14:39
uh you can train a neural network to
14:41
recognize
14:42
whether the product is is has a defect
14:45
or not and may and the class of defect
14:48
and so what this requires is
14:51
a large data set of images and it
14:54
requires them to all be classified
14:57
uh in order to train that neural network
14:59
uh
15:00
and typically that that requires a
15:03
person in the loop to do that labeling
15:05
of those images
15:06
so that you can train it and then the
15:08
neural network is a is a black box we
15:10
don't often
15:11
know what's going on inside of the
15:13
neural network how what it does to make
15:15
it

15:15
what it's using to make its decision and
15:18
we'll
15:18
we'll talk about each of these as we go
15:20
along but this is this is
15:22
this is good though because what the
15:25
image classification
15:26
can do is it can offload some of that
15:28
work that a human might be doing
15:30
so that the human can go uh uh take care
15:34
of other
15:35
uh use their skills in other ways inside
15:37
of manufacturing or
15:42
so so they can use their skills in other
15:43
ways inside of manufacturing and then
15:45
um but this is at the end of the process
15:48
so this is after
15:49
something has been made and there's a
15:51
lag between when the product is made and
15:53
when the inspection occurs and so
15:55
oftentimes one of the first questions
15:57
that comes up
15:57
is well can you tell me sooner i'd like
16:00
to know because i don't
16:01
want to wait until uh

16:04
i've potentially made 5 10 20 more
16:07
products before i get the feedback from
16:09
inspection
16:10
and so we can take uh an almost
16:13
identical approach
16:15
and apply it to sensor data coming from
16:18
the the machine that's doing that's
16:20
conducting the operation so in this case
16:22
a stamping press we might be collecting
16:24
pressure temperature vibration etc
16:27
it and again because this is a
16:30
neural network approach we have to train
16:32
it we need to have
16:34
uh e event data from the machine
16:38
and we have to be able to have it
16:40
classified to say
16:42
whether that was that led to a defect or
16:44
not
16:45
and then the neural network can learn uh
16:48
to to recognize patterns in that data
16:52
that
16:53
will lead to a defect and so we've moved
16:56
that further up the process we we still
16:59
haven't

16:59
necessarily prevented a defect from
17:01
occurring but we
17:03
we will have uh note identified
17:07
as soon as the first one occurs that
17:09
there that that there has been a
17:12
an issue in the process so that's so
17:14
that you can stop then
17:15
and not not make not continue to make
17:19
more
17:20
and there are ways to to further
17:23
analyze the the signal in order to
17:26
save more time to be able to perhaps
17:29
stop a long-running process before uh
17:33
you've wasted before you've spent eight
17:36
nine hours perhaps making product that
17:38
you can't use
17:40
and there's also ways of looking at how
17:42
the how the signals are trending
17:44
over time and being able to be more
17:46
predictive but those are that's a
17:48
that's you know another conversation
17:52
so one of the as i mentioned a neural
17:54
network is a black box it doesn't really
17:56
tell us what's going on inside of it how

17:58
it's making its decisions
17:59
so that's always a question that people
18:02
want is
18:02
okay so you tell me that there's a
18:04
problem can you tell me why there's a
18:05
problem
18:06
uh there are ways of doing this one of
18:09
which that's
18:10
uh that's fairly common and robust is
18:13
using a uh
18:14
decision trees or more broadly a random
18:17
forest
18:18
and similar training right so you still
18:22
have to have
18:23
that that curated data set that's all
18:26
been
18:26
labeled so that you can put it in and
18:28
train so that you can train your random
18:30
forest
18:31
to uh be able to recognize those defects
18:35
but the random forest is a little
18:38
different in how it's structured and
18:40
built
18:40
and that each node there's a decision

18:42
point at each node
18:44
and it takes it takes uh a feature of a
18:47
signal
18:48
and depending on the level of that
18:51
feature
18:52
it decides which path to go down the
18:53
tree in order to make its decision
18:55
and because of that we can come back and
18:58
uh
18:58
take a look at what it's doing during
19:01
that decision making process to come to
19:04
the conclusion at the end
19:05
so this can help us understand what are
19:08
the most important factors leading to
19:11
the decision for a particular defect
19:14
and so that helps understand the root
19:17
cause of where it's coming from
19:19
and uh that can drive decisions that
19:21
people make around how to go
19:22
correct it so all of what i've talked
19:26
about so far has been supervised
19:27
learning you have that data set you have
19:29
the labels that you use
19:31
um to to train the model

19:34
oftentimes we don't have those labels we
19:37
just we have data
19:38
and um so then we have to look at
19:41
applying
19:42
unsupervised techniques so uh
19:45
things like what um the the clustering
19:48
the k
19:48
nearest neighbors clustering approach
19:50
would be uh
19:52
considered an unsupervised technique um
19:56
as as dr schmitz was talking about a
19:57
moment ago and so
19:59
what we what this example is showing is
20:01
there's a
20:02
there's a a piston that's pumping of
20:05
pumping fluid
20:06
at a station on a line in a
20:08
manufacturing process
20:10
and there's an accelerometer that's been
20:13
mounted on
20:14
that that device and the
20:17
the spikes in vibration represent events
20:20
and so we use signal processing
20:22
techniques in order to be able to

20:24
uh divide this long continuous data
20:27
stream
20:27
into those different events and then we
20:30
can apply clustering just like dr smith
20:32
was saying
20:33
to be able to group those different
20:35
events
20:36
into categories so that we can better
20:38
understand
20:40
uh what's what the content of our signal
20:42
is so there's
20:44
what comes out of it is that there's uh
20:46
this
20:47
this curve that uh we don't really know
20:50
what it is we don't
20:52
at this point we don't really care why
20:53
or we don't really care what it is
20:55
we just label it generically event a it
20:58
happens a bunch of times
20:59
there's another thing called call it
21:01
event b it happens a bunch of times in
21:03
the data set and then there's this thing
21:05
that at first glance it gets grouped
21:08
together we call it

21:09
and it's event c but then we can run
21:11
that same clustering
21:12
again on each of these groups to see if
21:15
there are subgroups and what we find is
21:17
that there's actually two
21:18
subgroups of of uh event c
21:21
and so with this we can start to make we
21:24
can start to look for weird behavior in
21:26
the system so
21:27
so um in that event c
21:30
we can build an expectation based off of
21:33
what's the most commonly occurring
21:35
wave form for that particular event and
21:37
we'll
21:38
we'll call that our expectation and then
21:40
anything that doesn't
21:42
match to a degree with that expectation
21:45
we'll say that's
21:46
that's an anomaly that's something
21:47
different and
21:49
by tracking and and the the net result
21:52
of all this is that by tracking
21:53
those odd ones those those those
21:57
unexpected events and looking at how

22:00
frequently they're occurring and what's
22:01
the percentage that they're occurring
22:02
within a window of time
22:04
we can see this is this is showing that
22:06
so the the percentage
22:08
of those anomalous events uh within the
22:12
the subset we can see a a rise
22:15
uh at a point in time and
22:19
this this drop represents a period in
22:22
time in which the
22:23
the process stopped so uh and
22:27
we the reason we say this is
22:29
semi-supervised is because what happens
22:31
next we get the feedback that says
22:34
yeah that the line stops because there
22:36
is a
22:37
the the an incorrect fluid was put into
22:39
the system
22:41
and it happened roughly 24 hours before
22:45
the the line stops so we can see that
22:47
just by
22:48
taking this sort of naive approach of
22:50
identifying the anomalies
22:52
within those within that cluster of

22:54
signals uh
22:55
we can see a rise that gives us an
22:57
indication that something
22:59
is different about how that operation is
23:01
running and so then we can create an
23:03
alert
23:03
the alert doesn't necessarily say what
23:06
the problem is
23:08
and why but it does say hey there's
23:10
something uniquely different here that
23:11
people should be paying attention
23:13
perhaps even go take a look and we can
23:15
extend this
23:16
this semi-supervised approach even
23:19
further
23:19
to apply some more human knowledge about
23:22
the system to say
23:24
the the different features of these
23:26
curves represent different
23:27
aspects of the process and we can even
23:30
say
23:30
that you know the perhaps what's driving
23:34
the anomaly
23:35
condition is that this this piston

23:38
retracting the vibration is low during
23:40
that and that could
23:41
could uh indicate to the maintenance
23:44
people
23:45
what to go look at and it gives them a
23:47
better idea of what might be the problem
23:49
and what to fix
23:51
and so the the key takeaways of all of
23:53
this is to say
23:54
this these examples that i'm showing
23:56
we're only scratching the surface
23:57
there's so many different ways that we
23:59
can continue going and exploring and
24:01
extracting value
24:02
out of by using artificial intelligence
24:05
to analyze the data
24:06
and also there's no need to wait to get
24:09
started meaning
24:10
meaning each one of these came from data
24:13
sets that people
24:14
had within their operations and so you
24:17
can you can use those data sets and
24:19
and begin to get value so
24:22
that is that is it for me

24:25
thank you all for your time thank you
24:27
very much uh andrew for
24:29
the presentation um so now we are moving
24:32
on to the
24:34
next talk uh by kurt goodwin um kurt
24:37
is a humane mechanical engineering alum
24:39
and
24:40
he has over 40 years engineering
24:42
experience in
24:43
introducing and also developing new
24:46
technologies for jet engines gas and
24:49
wind turbines he has served as general
24:51
manager for advanced manufacturing and
24:54
now
24:54
although he is semi-retired but he's
24:56
still consulting with new manufacturing
24:58
and startups like beehive
25:00
3d so carrot take it away
25:04
okay and i think i'm sharing hopefully
25:07
you guys see some big engine blocks on a
25:11
yes perfect so i was about a far from uh
25:15
an artificial intelligence expert as
25:17
there is
25:18
a mechanical engineer i spent most of my

25:21
just as
25:22
as ali just said uh spent most of my
25:24
career
25:25
uh trying to help with the adoption of
25:26
new technology um
25:28
so i'm going to address sort of a people
25:31
aspect a little bit of
25:33
of how that does and and some ideas that
25:36
hopefully will help
25:38
help those of you that have something to
25:40
offer to to work with the
25:42
people more successfully a big piece of
25:44
my job has been
25:47
trying to help not just ai but different
25:51
digital
25:52
folks to understand manufacturing shops
25:55
and what drives them
25:57
early on we noticed that you know the
25:59
most successful groups in this area
26:02
had grown out of manufacturing
26:04
backgrounds or at least the teams
26:06
included large
26:07
numbers of people that had manufacturing
26:09
experience

26:11
because they understood their customers
26:14
um
26:14
and what their needs and the language
26:16
and drivers in a way that
26:18
you know somebody who's mostly done
26:21
software might not
26:24
i think it's interesting you notice both
26:25
tony and andy have that
26:27
experience themselves most factories if
26:31
you don't know this
26:32
are driven by fulfillment first
26:35
and second and to some extent uh
26:38
driven by cost it's a very tough
26:41
environment they're basically driven to
26:43
deliver
26:44
a product whether it's cars or medical
26:47
devices
26:48
or turbines or engines or whatever
26:51
every they're measured every week every
26:53
month every quarter
26:54
it's it's it's it's a tough
26:58
it's a tough uh business to be in
27:01
tech companies um come in and they might
27:05
be selling machine

27:06
monitoring parts flow better controllers
27:09
people who come in they do the
27:12
installations and then they fly home
27:13
friday morning sometimes
27:16
almost inevitably something goes wrong
27:19
the engineers and the workers in the
27:21
cell try and fix it
27:23
and if the tech company is there or
27:26
representative
27:27
things go well if if they're not there
27:29
they start trying to figure out how to
27:31
work around the glitch
27:33
um sometimes the outside helpers don't
27:36
even make it back the next week
27:38
and that's that that's the end of
27:40
cooperation
27:42
at the point where you're not able to
27:45
make product
27:46
and the people that are trying to help
27:48
you aren't there to help you
27:50
you've lost them forever that they're
27:52
not going to want to
27:53
work with you again
27:56
those companies that are successful

27:59
they know how to become part of the team
28:01
they understand that there are time
28:03
pressures
28:04
value being there when it's needed to
28:06
preserve shipment they've been stuck
28:08
doing 100 hour weeks themselves
28:11
um and so they they understand their
28:14
customers somewhat
28:16
the thing that you see over and over
28:18
from the most
28:20
successful people at doing this
28:22
regardless of the background
28:24
is they start out by talking to the guys
28:26
on the floor
28:28
and and working a shift with them they
28:30
don't try and hook everything up at once
28:32
if something does go wrong they ride
28:34
through it with them
28:36
um and basically
28:39
they they become they do everything they
28:42
can to put themselves in the
28:44
in the shoes of the people that are
28:47
working in the factory
28:49
so now whenever we work with startup

28:51
manufacturers like
28:53
beehive 3 additive that is mentioned
28:56
here
28:56
we try and start with a mix of people
29:00
that have those different backgrounds
29:02
manufacturing people that that have had
29:06
a lot of technology and and
29:10
digital experience and digital and tech
29:13
people that have worked on
29:14
on the factory doesn't have to be
29:16
anybody but if you can't
29:18
communicate between yourselves you can't
29:21
appreciate what's uh what's being
29:23
offered
29:24
it sounds simple right it doesn't sound
29:27
like this is any particular
29:29
revelation um but i've seen this
29:32
absolutely make and break a tech startup
29:35
or
29:36
a digital offering or a company that's
29:39
that's trying to get out there
29:41
um so what else um
29:45
if you can get past that startup
29:47
challenge if you can get the

29:48
relationship started
29:50
i think the next thing that's very
29:51
helpful is to try and
29:53
learn to think how to think about ai
29:57
um ginny rowdy who used to run ibm
30:01
had a comment that ai should stand for
30:03
augmented intelligence
30:05
the idea should not be that you're just
30:08
handing control over to an autopilot
30:10
which is kind of the way
30:12
some people describe some of this stuff
30:15
but rather that you have another set of
30:17
eyes and brains
30:19
on the floor to try and help you
30:20
understand what's going on
30:22
you know i think i think andy's point
30:25
is very similar to this
30:30
you don't necessarily know what you're
30:32
looking for to begin with
30:34
you try and collect the data that you
30:36
can
30:37
and and then think of it as more getting
30:40
help
30:41
noticing clues that might get missed

30:43
otherwise
30:44
so in in my experience many projects
30:47
start out with a very specific set of
30:50
instructions or goals to attack a very
30:53
specific perceived problem
30:55
you know one example is we're trying to
30:57
catch machine downtime
30:59
so we can get more throughput and up up
31:02
front there's an assumption or an
31:04
accepted idea that productivity is lost
31:07
because the machines are down
31:09
uh being fixed too much i had a great
31:12
example of this once we had a shop that
31:15
had
31:15
had to handle a big opportunity for
31:17
growth
31:18
in sales if they could only ship more
31:20
engines um
31:22
you put monitoring on a lot of machines
31:24
the data collections on times and starts
31:27
watch for
31:28
vibrations and events and oil
31:31
temperatures and so forth the first
31:33
the first breakthrough that came was

31:37
once we started mapping everything and
31:40
started understanding it
31:42
we discovered that a number of the basic
31:44
assumptions were
31:45
wrong you know so for example there was
31:48
a piece of equipment that gated
31:49
production
31:50
with very large engine block washer long
31:53
operation every
31:56
it had to go through a single machine
31:57
and every product had to go through it
32:00
on the good side of it um it didn't
32:04
break down very often
32:07
so you know the things like oil
32:09
temperatures and vibrations that we were
32:10
working
32:11
watching for didn't didn't turn to be
32:14
immediately useful but collecting the
32:18
information
32:19
um mapping times and and
32:22
flow through the shop um
32:26
you it still didn't deliver as much as
32:29
we
32:30
wanted from it so the data analysis

32:33
that that flagged that specific machine
32:36
it it one of the things that it was
32:38
noted was
32:39
that the it was often late starting
32:42
specifically during time periods around
32:45
the end of the morning or early
32:47
afternoon
32:48
so not not that it was breaking or
32:50
running right but for
32:52
some reason it would not be running
32:55
and consistently a certain set of times
32:59
it turned out to be a very simple
33:01
non-technical thing
33:03
that basically when the daily parts
33:05
delivery
33:06
truck came from the main factory the
33:09
operator
33:10
for that big machine that was needed
33:12
would
33:13
try and be a good guy and jump in and
33:14
help the crew unload it
33:16
so if the machine was already running it
33:18
was great it was no problem everything
33:20
kept

33:20
going we got flow beautifully
33:24
if not the start had to wait until the
33:26
operator finished unloading the truck
33:28
came back and got things started
33:30
the corrective action was about as
33:32
simple as it gets it was basically
33:34
hey george make sure the washer is
33:36
running before you do anything
33:38
or leave your station now you can argue
33:42
do you need ai to find that it's kind of
33:46
an irrelevant argument to me
33:49
because maybe you don't need it
33:52
but it had gone unnoticed before and the
33:55
data call
33:57
called attention to a specific time and
33:59
period and machine to investigate
34:01
and that's where i get the extra set of
34:04
eyes
34:04
helps speed up their the realization of
34:07
what you're looking at it
34:09
the other key thing to that is that's a
34:12
win
34:13
you need to celebrate it the first
34:15
reaction

34:16
when we found that basically we were
34:18
losing time because somebody was
34:20
unloading a truck
34:22
everybody wants to chastise somebody
34:24
else you know
34:25
you know the cell leader you shouldn't
34:27
have known this was a problem
34:29
the shop leader gets very defensive that
34:32
you know it seems like his uh
34:34
um his shop is out of control the
34:37
operators why did you let this happen
34:39
you should have needed a problem you
34:41
have to not let that
34:42
happen because if you don't recognize
34:47
that you've found an opportunity to make
34:49
things better
34:50
and encourage people to to
34:53
fix it work through it um
34:56
you know then you're you're not going to
34:58
get the feedback you need and people
35:00
will
35:02
actually not fudge the data but they
35:04
will
35:05
they will try and interfere with the

35:06
collection of data to be successful
35:10
so you know i think
35:13
if you can find the right ways to
35:15
encourage those kind of learnings and
35:17
applications
35:18
and and for everybody to be flexible
35:23
don't look at aei as a competitor or
35:25
something that's trying to take my job
35:27
but it's somebody else on the floor to
35:29
help me understand what's going on
35:31
and every time we get an improvement
35:34
it's a win
35:35
all that stuff will help
35:38
anybody on either side be more
35:40
successful
35:42
which is always the goal so that's it
35:45
thank you thank you very much kurt um
35:48
so now that you heard about academic
35:51
side and industry side
35:54
our last presentation is updating you on
35:57
what's going on in
35:58
national labs so it's my great pleasure
36:00
to introduce dr vincent parker a senior
36:02
research scientist in

36:04
electrical and electronic system
36:06
research division at oak ridge national
36:08
lab
36:09
uh his research is focused on computer
36:12
vision and
36:12
image processing with the periodic
36:15
election for
36:16
high performance image processing
36:18
algorithm development so
36:21
dr vincent please thank you thank you
36:24
very much so in the in this presentation
36:26
i'm going to cover a lot of the work we
36:27
do at the manufacturing demonstration
36:29
facility
36:30
i'm going to discuss the data we are
36:33
collecting
36:33
in the within the facility and the use
36:36
of ai
36:37
to process such data in order to answer
36:39
some of the scientific problems that
36:40
that we have in
36:41
in front of you of us so uh just uh on
36:44
my first slide
36:45
uh i will highlight the the link at the

36:47
bottom i don't know how i'm gonna be
36:48
able to share that with
36:49
with you all but there is a possibility
36:52
to have a virtual tour of the facility
36:53
where you'll be able to see
36:55
over a hundred thousand square feet uh
36:57
building
36:58
about 200 type of system that we that we
37:01
are working with
37:02
so for me as a data scientist this is a
37:04
fantastic playground because i get to
37:06
use to
37:07
play with machines of different types
37:10
and sizes and see how data-driven
37:13
methodologies can be used
37:15
in order to improve the systems or
37:18
assess the quality of the component
37:20
coming out of those
37:22
of the systems so that was
37:25
slide is not going to the next okay here
37:26
we go um so when when you work with this
37:29
type of of machine in the facility
37:31
you have example on the left-hand side
37:33
of the great thing that you can produce

37:35
with them
37:36
uh they look great this component this
37:38
car looks great
37:40
the the chevy cover looks great but at
37:41
the end of the day it's not necessarily
37:43
functional
37:44
and the problem with that is uh when
37:46
you're looking at critical components
37:49
you don't necessarily have a way right
37:51
now
37:52
to tell what's coming out of the machine
37:54
is actually of great quality without
37:56
doing
37:57
any kind of non-destructive evaluation
37:59
of really expensive
38:01
testing in order to validate the
38:03
component which
38:04
in the at the end of the day uh kills
38:06
the business case for
38:08
for additive altogether and and so our
38:11
interest here is to see
38:13
if there is any mechanism using data
38:16
to get a better understanding of the
38:18
process so we can develop

38:20
certification methodologies for those
38:22
components but ultimately come up with a
38:24
way to accelerate production of those
38:26
components and improve the manufacturing
38:28
technologies all together
38:29
so we are taking a a traditional smart
38:32
manufacturing approach where you try to
38:33
understand the process optimize it
38:35
eventually implement feedback loop
38:37
control mechanism if you can correct
38:38
your process on the fly
38:39
and ultimately that will lead to a
38:41
scenario where you'll know so much about
38:43
your process and you control your
38:45
process
38:46
so well that you will be able to tell
38:48
this component coming out of my machine
38:50
i don't need to test it because i know
38:52
so much about it that i can say
38:53
it's it's actually a good component so
38:56
in order to do that
38:58
you need to uh have a lot of data and
39:00
and that's really where
39:02
our our wheel hours here uh is so we

39:05
want to make sure that we can collect
39:07
information at any given step of the
39:09
manufacturing process
39:10
this slide is going to get extremely
39:11
busy in a second i don't want you to
39:14
try to dissect everything but just
39:17
it's here to give you an idea of the
39:19
type of information we are interested in
39:21
collecting so if you have a goal for
39:22
example to produce an n95 mass which is
39:25
something that we did
39:27
you're going to be looking at a
39:29
different type of design
39:33
excuse me modeling and simulation for
39:35
past planning
39:37
before you send this to the printer as
39:39
with the same time as the as the
39:40
feedstock
39:41
and every time you're going through this
39:43
this chain you're going to be collecting
39:44
information about the the printer itself
39:47
instrumenting the printer to look at
39:48
what's happening inside it doing data
39:50
registration and anomaly detection

39:52
in order to analyze this data and then
39:55
you have your
39:56
first component printed you're going to
39:57
chop it into pieces
39:59
and go through subsequent steps of
40:00
post-processing
40:02
testing and so on in order to create
40:04
what we call a digital clone of the
40:06
physical component
40:07
so you're going to have at this point
40:08
the entire history of your component
40:10
contained in a data package
40:12
and you will be able to use this data
40:14
package for visualization purposes or to
40:16
feed a larger database
40:18
that as it grows will help you
40:20
understand better what's going on
40:21
in in your manufacturing process when
40:23
you do inter builder intra build uh
40:26
machine learning you're gonna be able to
40:28
then go back
40:29
and say okay now i can i can start
40:32
predicting the performance of my
40:33
component because i've learned so much

40:34
about my process
40:36
but also act on the design itself and
40:39
help uh some of the the the cad software
40:42
to produce
40:43
uh design that are also optimized for um
40:46
with material science knowledge in mind
40:49
so
40:51
in order to get there you don't want to
40:53
reproduce this for every single system
40:55
so you need to come up with a unified
40:57
data architecture that will help you
40:58
collect such information
41:00
and the way we see this is to look at a
41:02
component
41:03
as a massive building block set and what
41:05
you're doing really with the machine
41:07
is to tell the the system grab this
41:10
block and
41:11
of this particular color and put it at
41:13
this particular location in space
41:15
when you do this you have data that
41:17
tells the machine
41:18
or you have you have processes that tell
41:20
the machine how to do this

41:21
but you can also collect the data on the
41:23
system to know how the machine actually
41:25
perform
41:25
and so that's coming from the different
41:27
data producers let me get a laser
41:29
pointer here
41:32
for some reason i can't that's
41:35
interesting
41:37
looks like they've changed the system i
41:39
don't know um so
41:41
um you you're going to have different uh
41:43
uh data producer you're going to be
41:44
collecting this data and each
41:46
uh each data producer will provide you
41:48
one value or multiple values that can
41:50
then store for each xyz location
41:52
so now you have a feature vector of
41:54
information that describes each element
41:55
in space
41:56
which is a fantastic scenario for any
41:59
kind of machine learning type of
42:01
of applications so when you have all
42:03
these data packaged together
42:05
you can do anything that's listed on the

42:06
right-hand side of this line
42:08
and so with that i'm going to go through
42:10
some of the examples on how you can use
42:12
this data
42:13
so first and that was touched on by uh
42:16
dr anderson
42:17
um uh you can uh observe what's
42:20
happening inside your powderbed system
42:22
so if you have for example
42:23
an image like this you're gonna be able
42:25
to see what's what's
42:26
uh what's happening you can see certain
42:28
type of features and what you want to do
42:30
is classify those voxels
42:32
or pixels in this particular case
42:35
for to identify the type of of classes
42:39
they belong to
42:39
so that's kind of the first phrase that
42:41
we had we moved on to
42:42
something a lot more advanced where we
42:45
train a unit in this particular case
42:47
to take a stack of of of images of from
42:51
multiple modalities train the model and
42:54
then the model spits out a

42:56
map of all the the the defects
42:59
that you are defects or features that
43:01
you are interested in detecting
43:02
so when you scale that up to the size of
43:04
the component you can render in
43:06
in 3d an entire map of all the features
43:09
that are present in
43:10
in this particular component and you can
43:13
then help
43:14
operators of the machine uh see things
43:17
that are
43:18
happening when they are printing their
43:20
their parts and see if they can
43:22
modify the process in order to get
43:24
better results
43:26
the thing that's interesting with this
43:27
and that goes along the the comment that
43:28
we
43:29
made before uh this gentleman in front
43:32
of the computer here is
43:33
he's an operator of a machine he has no
43:35
computer science background
43:37
but you can provide them too that they
43:39
can help them

43:42
become better operator of the system
43:43
it's not again
43:45
to replace the operator of the system
43:46
it's having a computer helping you
43:49
being better at you at your job and so
43:51
he's training his own models with the
43:53
platform we put in place so that's a
43:54
that's a nice way to
43:56
use ai in this in this particular case
43:59
a direct example or a direct use oops
44:02
two slides a direct use of this
44:04
particular
44:06
type of of models is you can start
44:09
looking at
44:10
automating correction on the machine so
44:12
for example on the binder jet system
44:13
like this one
44:14
we use exactly the same techniques
44:16
putting cameras to
44:17
get different modalities of the sensor
44:20
of the
44:20
of the process uh classified the data to
44:23
get
44:23
in green the part and in in purple it's

44:26
incomplete spreading
44:27
that's a defect that's fairly easy to
44:29
engineer uh on the on the machine
44:31
so in this particular example here what
44:34
you have is
44:34
in the x-axis the number of the layer
44:37
number
44:38
you're going up as you're going from
44:41
left to right
44:41
and here you have the percentage of
44:43
pixels that we are uh
44:44
of a given color so in this particular
44:47
case what we did we we forced the
44:48
printer to create an
44:50
incomplete spreading so you have a
44:52
percentage of of pixel that increases
44:55
roughly from two percent at the
44:56
beginning to a quarter of the image was
44:58
covered with
44:59
with purple pixels at this point we turn
45:01
on the
45:02
switch and say okay now it's ends off
45:04
and we're going to let the ai takes over
45:06
and change the process parameters in

45:08
order to go down
45:09
and remove this particular defect and
45:11
and you can see the curve is going down
45:13
to a level that is actually lower than
45:15
where it started so you can use ai
45:18
for some of those uh particular defects
45:21
and make sure that you don't have an
45:22
operator in front of the machine
45:24
at all time in order to correct for for
45:26
some of the
45:27
of those problems that are actually
45:29
fairly straightforward and easy to
45:32
uh to correct if you cannot implement ai
45:34
for this type of correction you can
45:36
however send messages to operator of the
45:39
system make sure that they
45:40
they see this another place where we use
45:43
ai is on ct reconstruction
45:45
so the advantage of of additive is that
45:48
you know
45:49
the the the overall shape of your
45:51
component and you can use that at your
45:53
advantage in order to help with ctrl
45:55
construction of these samples

45:57
so if you use a traditional ctr
45:59
construction algorithm this is an
46:01
example of what you're going to get
46:03
but we've developed a technique that's
46:05
that's mixing
46:06
prior knowledge or design knowledge of
46:09
the component
46:10
and some data that we've collected
46:14
across multiple builds in order to train
46:16
a model that will uh
46:18
just give you a overall better
46:20
reconstruction of your component with
46:22
less noise air and more defined
46:24
uh defects detected within the the
46:27
geometries
46:28
those are actual two exact uh um
46:32
reconstruction example this is a
46:34
traditional reconstruction and this is
46:36
what we're getting out of our of our
46:39
models um one of the thing that we are
46:43
also interested in doing is
46:45
is pushing the machine to do things that
46:46
are not supposed to do
46:49
so if you look at a design like this and

46:51
you print it in a particular
46:53
system in this particular case it's an
46:55
electron beam machine from arkham
46:57
if you print pencil bar at the bottom
46:58
and at the top and you use the black box
47:00
of the machine that's provided by the
47:02
manufacturer
47:03
it will print but it's not going to
47:04
produce the same component they're going
47:06
to look the same
47:07
they are not going to perform the same
47:08
if you take micrographs out of those
47:11
cylinders they are circled with the same
47:13
color here you see two different type of
47:15
texture which is well known
47:17
is directly uh uh gonna be correlated to
47:20
the type of mechanical test you're gonna
47:21
get so you're you're seeing two
47:23
different type of clusters
47:24
not same results however you've
47:26
collected enough data to
47:28
learn different type of patterns that
47:30
will lead to the production of certain
47:32
type of microstructure growth or other

47:33
type of microstructure groups
47:35
and so you can use this in order to
47:37
fine-tune the
47:39
process parameters and apply a
47:41
particular type of
47:42
a manufacturing process depending on the
47:45
cross-section of your geometry that you
47:46
are
47:47
so that's something that that oops sorry
47:50
i'm going to come back okay so that's
47:53
something that that we did here
47:54
and those examples here is printing
47:57
again the same geometry we pulled again
47:59
micrographs from from tensorboard the
48:01
bottom and the top
48:02
and you can see the microstructure are a
48:04
lot more similar
48:05
and the uh mechanical tests are
48:08
actually clustered together so this
48:11
um this is how you take control of your
48:14
manufacturing process so now it's not
48:16
random anymore
48:17
it's not you're not at the mercy of the
48:19
decision of the engineer of the

48:21
that that put together the machine or
48:23
the programmer that put together a
48:25
software that runs the machine
48:26
you're already in control of what you
48:27
want to get out of the system
48:29
and when you have this level of
48:31
understanding you i don't even need to
48:33
to test those samples anymore because i
48:34
know what i'm going to get
48:36
direct application of this we've used
48:39
this type of approach and it's been
48:41
accepted
48:42
by by industry as ai has been accepted
48:45
by industry in this particular case
48:47
to validate some of the components that
48:49
were produced so we have two examples
48:50
here one with solar turbines
48:52
where we printed over 200 uh turbine
48:55
blades
48:56
and use the the the the tools that i've
49:00
highlighted before
49:01
in order to identify which blades were
49:03
of the highest quality
49:05
80 of them went to a stress test and

49:08
then on the hot fire tests
49:09
on august 25th and they perform as as
49:13
expected as well as traditionally uh
49:15
manufacturing of component
49:16
another case is something related to a
49:19
large program that we have at the
49:21
at the lab which is the transformational
49:24
challenge reactor where we are working
49:25
on
49:29
we are working on on printing uh
49:31
components
49:32
uh for nuclear type of applications we
49:35
had
49:35
uh as part of this program a
49:37
collaboration with
49:38
framatum and the tennessee valley
49:41
authority
49:42
to print component that will go into a
49:44
commercial reactor and you have a
49:45
picture of them
49:47
and they were they went through the same
49:49
type of of
49:51
tests i or evaluation i mentioned uh
49:53
before

49:54
they went to however traditional um
49:58
nd testing in order to make sure that
50:00
what we said was actually correct
50:02
and they were approved and they went
50:03
into the the
50:05
the commercial reactor at the end of
50:07
last year
50:09
so what's next for a manufacturing data
50:12
science and probably
50:13
more in particular for uh in terms of of
50:16
ai
50:16
they i mean kind of mentioned that uh
50:19
earlier
50:20
on on the material inform generative
50:23
design so
50:24
we we do have generative design type of
50:27
algorithm right now
50:28
that are great to simplify or change the
50:31
way we we design uh components
50:33
but they are not necessarily including
50:35
enough of the material information that
50:36
we can we can collect
50:38
and so that's something that we're
50:39
interested in in pushing the augmented

50:41
intelligence portion again uh the
50:44
the next generation of the of
50:46
manufacturing uh
50:48
uh operators uh will leave with a
50:51
computer
50:52
alongside them and so we need to have a
50:55
system that can help them do
50:57
uh what they what they do best i'm not
50:59
going to go in detail through all of
51:01
this the one i will
51:02
highlight that is more related to the
51:05
control of a microstructure
51:07
is the full optimization of what you are
51:09
actually doing
51:10
and making sure that you you engineer
51:13
your manufacturing material properties
51:15
in space and not solely manufacturing
51:17
components
51:17
and with that i'm at the end of my
51:19
presentation and i will welcome
51:21
questions thank you very much
51:25
vincent um so i would like to thank all
51:27
the speakers again
51:28
for the great presentations and now we

51:31
are
51:32
moving into the question and answer
51:34
period so um
51:36
thank you everybody for posting the
51:38
questions uh there so i will start with
51:40
the first question
51:42
for tony so what is the biggest
51:44
challenge that you see for implementing
51:47
ai into manufacturing domain
51:50
well if we are using a classification
51:53
approach
51:54
you'd like to have an automated
51:56
technique
51:57
for classifying that data right
51:59
otherwise you've sort of defeated the
52:00
purpose if i have to look at every
52:02
signal
52:03
and decide what happened so i think
52:06
that would be a an obstacle
52:11
for widespread implementation and that
52:14
you know
52:15
i tell you what's interesting is that
52:16
you bring in the domain
52:18
experts with the machine learning

52:20
experts and i think that collaboration
52:22
is essential
52:23
great thank you very much and next
52:26
question
52:27
is um for vincent
52:30
um what would be a possible approach
52:33
when the system
52:34
don't have a well-defined physics-based
52:37
model so if there is too many unknowns
52:39
for example in the case of 3d printing
52:42
we've seen in the in in the past that a
52:45
lot of the
52:46
physics based model for some of the the
52:48
technologies are not
52:50
um are overly complex and not
52:53
necessarily correct
52:54
uh at the end of the day and so the way
52:56
we approach this so for example for the
52:58
microstructure control i mentioned
53:00
we we've used high physics based models
53:03
uh to get there but really realized that
53:07
it was better to go
53:08
through a in-situ monitoring approach to
53:12
better understand what was happening for

53:14
a variety of combinations
53:17
of the um of the
53:20
of the manufacturing process and work
53:22
with lower order models in order to
53:25
get a an answer
53:29
they are like a lot of those models
53:32
that that seem to be right uh but
53:36
when you apply them at large scale first
53:39
sometimes you can't
53:40
because you can you cannot compute uh uh
53:43
the the the result for for a large
53:45
component
53:46
uh and and sometimes they are overly
53:48
complex it's not necessary
53:50
so good do finding a good balance
53:53
between
53:55
what sensor will provide you and what
53:57
models
53:59
rightly uh selected and applied to
54:02
sub region within your within your
54:04
geometry is probably a better approach
54:07
for for most systems thank you very much
54:11
and next question i'm going to ask
54:13
andrew um

54:15
so we talked about neural network you
54:17
know and different approaches so
54:19
in terms of like being in industry what
54:22
kind of ai or machine learning tools
54:25
um is mostly used in industry and how do
54:28
you decide which one of those
54:30
is appropriate for your application so
54:32
the uh
54:34
in terms of what's most common i mean i
54:36
i i'd probably have people arguing with
54:38
me about linear regression being an ai
54:40
tool but i
54:41
i would uh it's a way of of defining a
54:44
model of something so
54:45
i i mean that one's been there for a
54:47
long time uh but in terms of like what
54:49
we consider
54:50
advanced ai i think we're seeing a lot
54:52
more neural networks come up there are a
54:54
lot of people
54:55
asking for that use case at the very
54:57
beginning where i've got images of
54:58
products i want to classify if they're
55:00
defects or not

55:01
um beyond that i mean
55:05
they they all have their different um
55:08
their different
55:09
use cases unsupervised techniques
55:11
because you often
55:12
don't know what you don't know so let's
55:15
go
55:16
do some signal processing and then let's
55:19
group them together
55:20
and then review those results and though
55:23
then you have aha moments where you say
55:25
oh well i yeah of course that makes
55:27
sense to me that
55:28
that those things would be grouped
55:30
together or
55:31
um or the there's a
55:34
there's some press they're using like a
55:37
markov chain or some sort of thing you
55:39
might be able to determine precedence of
55:41
events or
55:42
the the sequence of events and says of
55:43
course now it all makes sense that that
55:46
those things happen
55:47
in that order so i don't i don't know

55:49
that that's a
55:50
great answer to what's the most
55:51
prevalent but it's to say that there's a
55:54
lot
55:54
of different techniques that people are
55:56
applying
55:57
that's great thank you very much andy
55:59
and the next question i'm going to ask
56:01
kurt um
56:02
you mentioned about um the other way of
56:05
looking at ai
56:06
as instead of saying artificial
56:08
intelligence we talked about it as
56:10
augmented intelligence right
56:12
and i got a comment from one of our
56:14
attendees dr terry you
56:16
mentioning that in 1994 acm
56:19
and newell award acceptance speech
56:21
frederick brooks also mentioned
56:23
something very similar
56:24
and called ai as ia or
56:27
intelligence amplification so
56:30
the question is that since you have a
56:32
lot of experience in industry

56:35
where do you think the industry will
56:37
benefit most from incorporating ai
56:41
and not just from technological point of
56:42
view from the acceptance point of view
56:45
from the engineers who are on the floor
56:47
so they don't feel
56:48
they're losing their jaws but right they
56:50
see that there's somebody helping them
56:52
right i think that's one of the reasons
56:54
that i like
56:56
the augmented uh um intelligence idea i
57:00
saw that comma i thought that was great
57:02
i
57:02
i stole it for another day um i
57:05
i think anything
57:09
that overcomes the initial
57:12
doubt is helpful there's there's a
57:15
and and i think it's been unfortunately
57:20
provoked to some extent by a lot of
57:22
discussion in the in print and in the
57:23
media
57:24
where people seem to want to get people
57:28
afraid of robots
57:29
i i think once people

57:32
[Music]
57:33
working in any shop run into a success
57:37
and start to see the opportunities for
57:41
it
57:43
as being help and not competition
57:48
it that that overcomes any
57:51
doubt or sales pitch better than than
57:55
you know anything you can say so we
57:58
you know i have a colleague who likes to
57:59
talk about getting base hits
58:01
um you don't have to solve world hunger
58:04
the first time out the first time
58:06
you uh you know they work with somebody
58:08
like tony and he helps them
58:10
not break tools off anymore because
58:12
they're driving the machine too hard
58:15
or uh i know andy's had some great use
58:19
cases on
58:20
on recognizing unrecognized limits
58:24
those breakthroughs do more to win
58:27
people over
58:28
than all the talk you can imagine
58:31
um but i think starting out by even the
58:34
best way to start out is to just

58:37
just to say well look these are not here
58:39
to replace you
58:41
these are here to help us find problems
58:44
and fix them
58:45
and get through it and then look for
58:48
that chance to show everybody
58:50
that's the best thing i know thank you
58:53
very much kurt um
58:54
we are at time so i just want to mention
58:56
that um i would like to thank again all
58:58
the speakers all of you attend this for
59:00
attending this event if you liked
59:02
this event ai for manufacturing you can
59:05
join us
59:06
on the first thursday of every month in
59:08
april we have ai for agriculture
59:10
in may we have ai for health care and in
59:13
june we are going to present multiple
59:15
projects which are funded by the umen
59:17
aic grant
59:18
i also want to thank our sponsor office
59:20
of vice president for research
59:22
sponsoring university of maine ai
59:24
initiative

59:25
and also my colleagues at the ais
59:28
student committee
59:28
doctors susan mckay terry you roy turner
59:32
sharmila mohapadi charlene jen saul
59:34
allen and jason sharland
59:36
and also in the background i would like
59:39
to thank
59:40
office of research help that we got
59:44
melinda pelletier who is actually
59:46
running the background zoom here for us
59:49
um i know we have a few more questions
59:51
but we are out of time so we will
59:53
answer those offline and again don't
59:57
forget to
59:59
respond to the survey requests we'll
60:01
send out later so
60:02
hopefully we'll make these events better
60:04
so thanks again all the speakers and
60:06
attendees and enjoy the rest of your day
60:08
have a great day

The University of Maine in Orono is the flagship campus of the University of Maine System, where efforts toward racial equity are ongoing, as is the commitment to facing a complicated and not always just institutional history. The University recognizes that it is located on Marsh Island in the homeland of the Penobscot nation, where issues of water and its territorial rights, and encroachment upon sacred sites, are ongoing. Penobscot homeland is connected to the other

Wabanaki Tribal Nations — the Passamaquoddy, Maliseet, and Micmac — through kinship, alliances, and diplomacy. The university also recognizes that the Penobscot Nation and the other Wabanaki Tribal Nations are distinct, sovereign, legal and political entities with their own powers of self-governance and self-determination.