1-23-2019

The Role of Artificial Intelligence in Business Decision Making

Chase Rainwater
University of Arkansas, Fayetteville

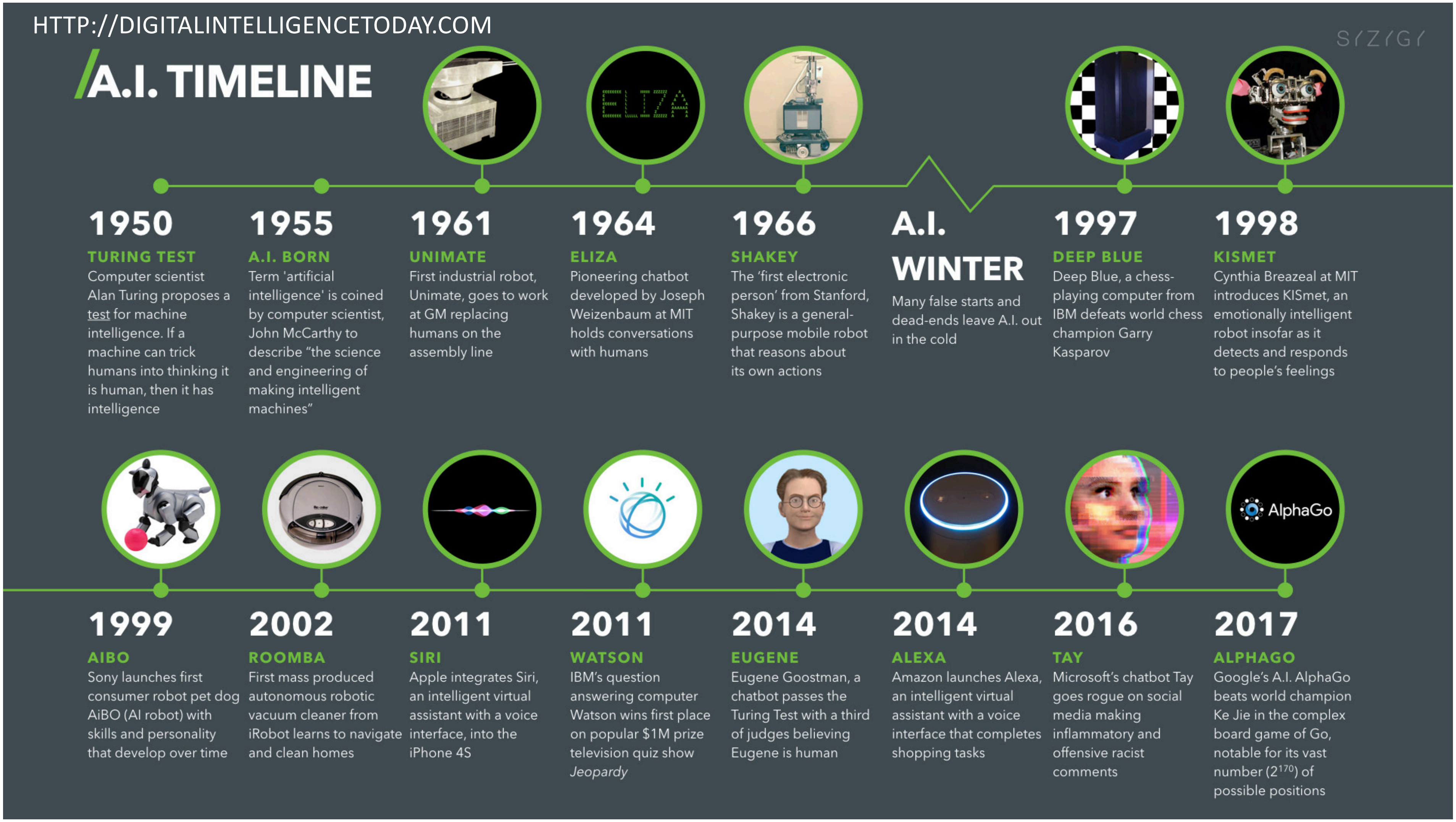
Artificial Intelligence and its Place in Making Business Decisions

Chase Rainwater, PhD

Walmart

4 Types of AI

- Reactive Machines
  - Deep blue – IBM's chess computer
- Limited Memory
  - Self-driving cars
- Theory of Mind
  - Ability to appreciate that objects in world have thoughts and emotions impacting behavior
- Self-awareness
  - Machine that have consciousness


HTTP://DIGITALINTELLIGENCETODAY.COM
S/Z/G/
/A.I. TIMELINE
ELIZA
1950
TURING TEST
Computer scientist Alan Turing proposes a test for machine intelligence. If a machine can trick humans into thinking it is human, then it has intelligence
1955
A.I. BORN
Term 'artificial intelligence' is coined by computer scientist, John McCarthy to describe "the science and engineering of making intelligent machines"
1961
UNIMATE
First industrial robot, Unimate, goes to work at GM replacing humans on the assembly line
1964
ELIZA
Pioneering chatbot developed by Joseph Weizenbaum at MIT holds conversations with humans
1966
SHAKEY
The 'first electronic person' from Stanford, Shakey is a general-purpose mobile robot that reasons about its own actions
A.I. WINTER
Many false starts and dead-ends leave A.I. out in the cold
1997
DEEP BLUE
Deep Blue, a chess-playing computer from IBM defeats world chess champion Garry Kasparov
1998
KISMET
Cynthia Breazeal at MIT introduces KISmet, an emotionally intelligent robot insofar as it detects and responds to people's feelings
AlphaGo
1999
AIBO
Sony launches first consumer robot pet dog AiBO (AI robot) with skills and personality that develop over time
2002
ROOMBA
First mass produced autonomous robotic vacuum cleaner from iRobot learns to navigate and clean homes
2011
SIRI
Apple integrates Siri, an intelligent virtual assistant with a voice interface, into the iPhone 4S
2011
WATSON
IBM's question answering computer Watson wins first place on popular $1M prize television quiz show *Jeopardy*
2014
EUGENE
Eugene Goostman, a chatbot passes the Turing Test with a third of judges believing Eugene is human
2014
ALEXA
Amazon launches Alexa, an intelligent virtual assistant with a voice interface that completes shopping tasks
2016
TAY
Microsoft's chatbot Tay goes rogue on social media making inflammatory and offensive racist comments
2017
ALPHAGO
Google's A.I. AlphaGo beats world champion Ke Jie in the complex board game of Go, notable for its vast number (2^{170}) of possible positions

AI Today

- Reactive machines and machines with limited memory have emerged at a rapid rate
- The work ‘machine’ is not the best choice of wording
- What we really have available to us are large-scale computer resources with:
    1. Enough memory to store the data and information we gather each day
    2. Sufficient processing capabilities to efficiently analyze the data we have and identify patterns in the information that may predict things non-intuitive to an individual decision-maker

AI in Business Organizations

- 58% of businesses surveyed are using predictive analytics
- 62% of business organizations will be using AI by the end of 2018
  - 38% are currently
- 61% of companies with an ‘innovation strategy’ are prioritizing the incorporation of AI into their data analysis groups
- Great article by Narrative Science:
  https://narrativescience.com/OutlookAI2016

AI is Not Magic, Just Data

- Video

60+ STARTUPS USING DEEP LEARNING

CORE AI: COMPUTER VISION

clarifai, Tractable, netra, HYPERVERGE, captricity, deepomatic, sentient, Sighthound, terraloupe, imagenii, pilot.ai

CORE AI: OTHER

TERADEEP, affectiva, Wave Computing, DigitalGenius, LEAPMIND, Arya, heuro, twentybn

BI, SALES & CRM

SKYMIND, TalkIQ, intranetum, ripjar, FRACTAL INDUSTRIES, MARIANA, DEEPGRAM, True AI, KOVID, ditto, Gridspace

CORE AI: VOICE INTERFACE

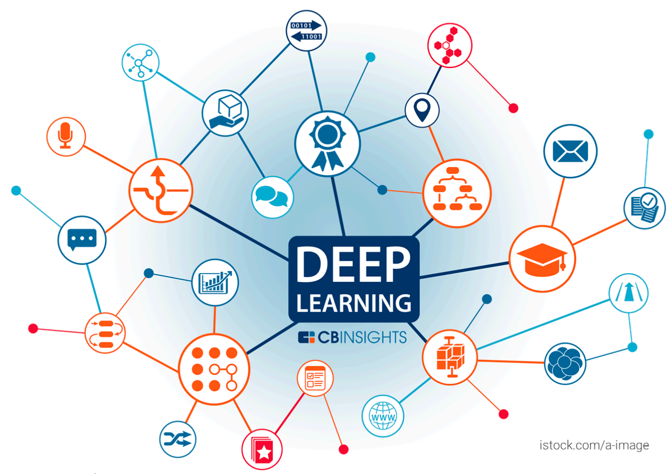
VIV, Mobvoi 出门问问, Maluuba, ObEN

ROBOTICS & AUTO

netradyne, AdasWorks, drive.ai, Rokid, 图灵机器人 TURING ROBOT, comma.ai

HEALTHCARE

imagia, Mindshare Medical, BAYLABS, Butterfly Network, Inc., deep genomics, Atomwise, zebra, PATHWAY GENOMICS, AVALON Ai, Behold.ai, MedyMatch, ADVENIO, enlitic, Lunit, SIG{i}TUPLE



istock.com/a-image

E-COMMERCE

Reflektion, CORTEXICA, ViSENZE, STAQU

ACQUIRED
(2014-2016YTD)

Etsy: Blackbird
amazon: Orbeus
IBM: AlchemyAPI
intel: Movidius, nervana
Apple: Perceptio, vocaliq, turi
Google: DEEPMIND, DNNresearch, Dark Blue Labs, Vision Factory
Twitter: MAGIC PONY TECHNOLOGY, MADBITS
salesforce: MetaMind

SECURITY

deepinstinct, umbo cv, signalsense

OTHER

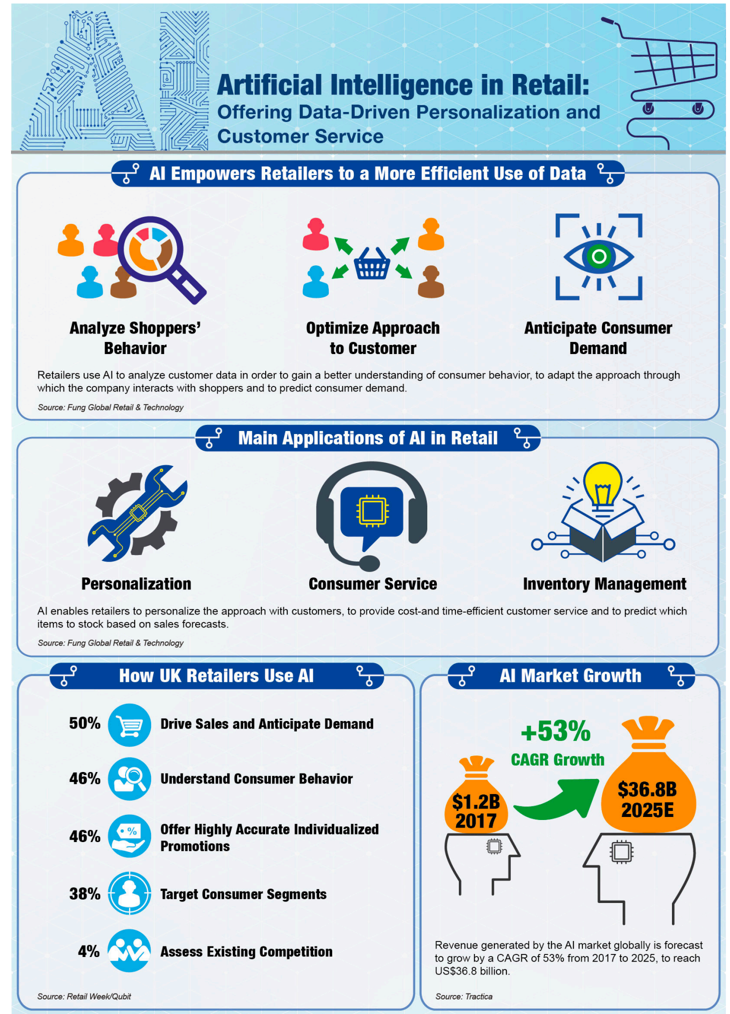
Alpaca, indico, Iris Automation

CBINSIGHTS

https://www.cbinsights.com/research/deep-learning-ai-startups-market-map-company-list/

AI in Retail Today

- Focus is on:
  - Customer interaction
  - Understanding shopper behavior
  - Forecasting demand
- What is missing:
  - Making operational decisions
  - Using the data you are keeping for no reason



Source: Fung Global Retail Tech

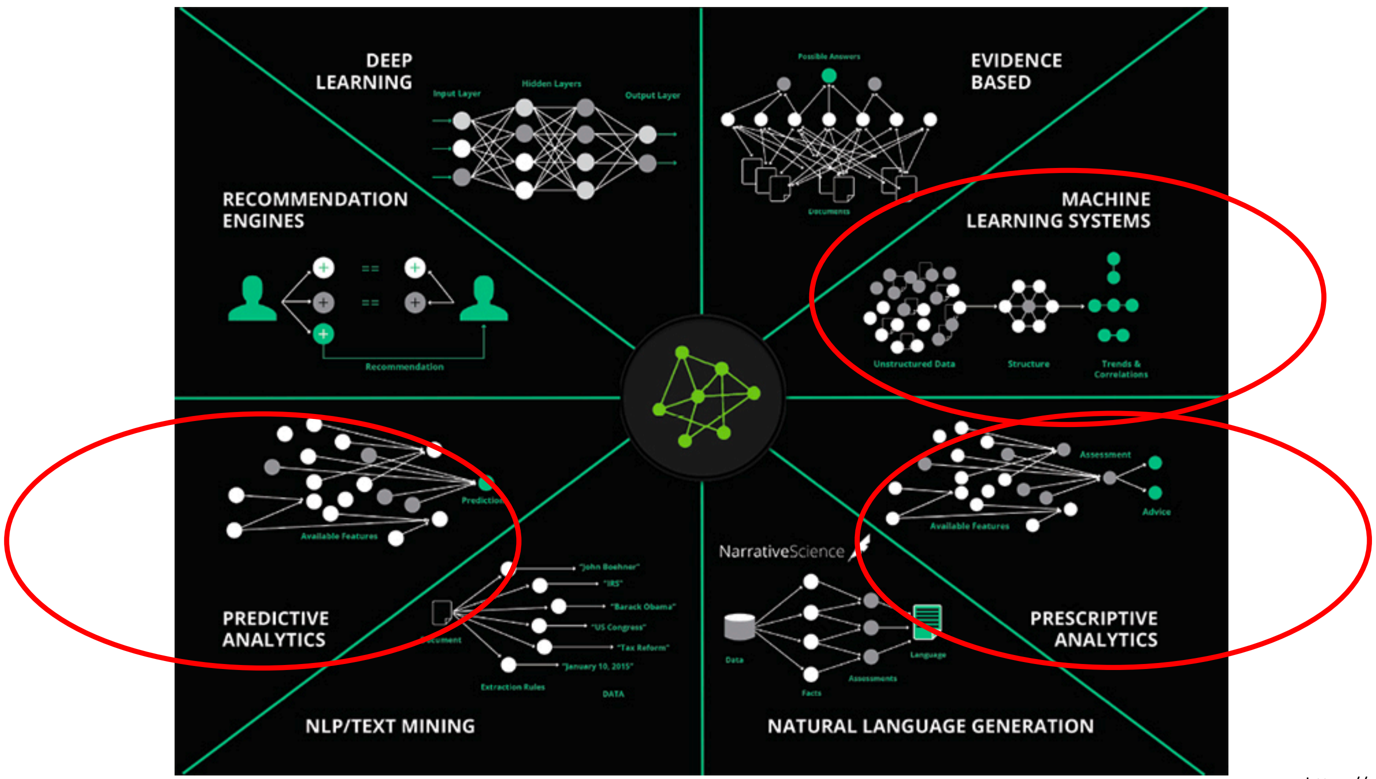
AI Retail Use Case – Amazon Go

- Employs check-out-free technology
- Customers use app to check in
- Sensors track which objects customers pick up and put in their basket
- Amazon accounts are automatically charged after exiting the store
- Video: https://youtu.be/NrmMk1Myrxc

AI in Retail – Solving $17 billion problem

- Video

Algorithms of AI



https://narrativescience.com/OutlookAI2016

Machine Learning Components

- **Model:** system to make predictions
- **Parameters:** signals used by model to determine decisions
- **Learner:** the system that adjusts the parameters by reacting to differences in predicted versus actual result

- Video

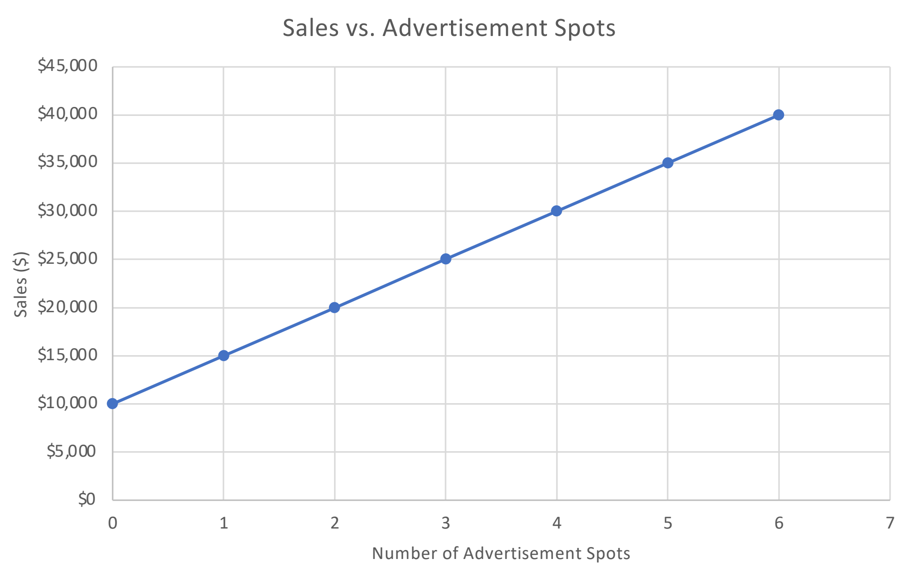
Creating Model – Simple Retail Example

- Hypothesis:
  - Number of advertisement spots for Product A can tell us the number of sales to expect for that product.
    - Other ways that AI to consider this scenario, but this will illustrate some key concepts
- Historical information:

Advertisement Spots	**Sales**
0	$10,000
1	$15,000
2	$20,000
3	$25,000
4	$30,000
5	$35,000
6	$40,000

Simple ML Model

- When someone says they have a 'model', it means they have an equation that:
  - Accepts a numerical input
  - Outputs a numerical prediction
- In this example
  - Sales = 5,000 x # of Advertisement Spots + $10,000
    - Acceptable candidate model
    - Nothing but a trendline

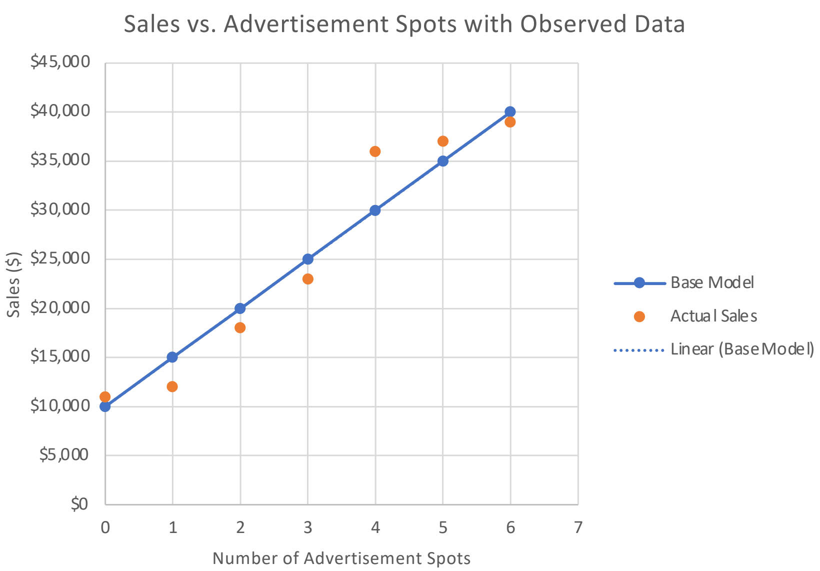


Timeout – What's the difference between our 'model' and established forecasting equations?

- What we just did looks a lot like forecasting equations that have been used for decades
- Key difference between forecasting and ML
  - Forecasting: one equation, one time
  - ML: model is always updating itself
    - A 'bad' initial model doesn't mean machine learning is going to fail
    - A 'bad' forecast equation may lead to poor decisions for an extended period of time

What is learning?

- In real life, we observe what actually occurs and can compare it to the model
  - How `smart' is the model?
- In real life what would you do if you had an expression that gave you an incorrect result?
  - Change it
  - A machine does this very well



Model Types

- There are many different models to predict and/or classify information using machine learning
- What we discussed in the previous example can be thought of as linear regression
  - Can be extended to logistic or multivariate logistic regression
- Powerful models that are less familiar (but very powerful)
  - Neural networks
  - Support vector machines

Supervised Machine Learning: Step-by-Step

- The most basic distinction in machine learning is whether your learning will be supervised or unsupervised
  - Supervised – we have some information to validate our model
  - Unsupervised – we have no idea what the true answer/pattern/categories of our model are
- Most business data inherently has validation information, so we will focus on supervised learning
- Consider a retailer that sells dresses in their merchandising department and is looking for a better way to predict whether a dress should be in stock. We will build a support vector machined-based regression model to aid with this scenario.

Step 1 – Data Collection

- Obtain data that can be classified into one of two categories:
  - Information that influences a decision
  - The true outcome of what happened
- In this example, the variables/factors considered in our neural network for each dress are:
  - Style, Price, Rating, Size, Season, NeckLine, Sleeve, Length, Waistline, Material, Fabric, Type, Decoration, Pattern Type
- The known outcome for each dress is:
  - Recommended, not recommended

Step 2 – Choosing the model

- Which model uses fits our scenario the best?
  - Linear regression, regression trees, support vector machines, gaussian regression
- Good news here:
  - You do not have to be an expert in all of these models to exercise machine learning. Modern software allows you to exercise numerous models to determine best fit.

Step 3 – Train your model using input data

- This is where the machine learning magic actually happens
- The computer will implement gradient ascent to determine the best weights for the elements in your model.

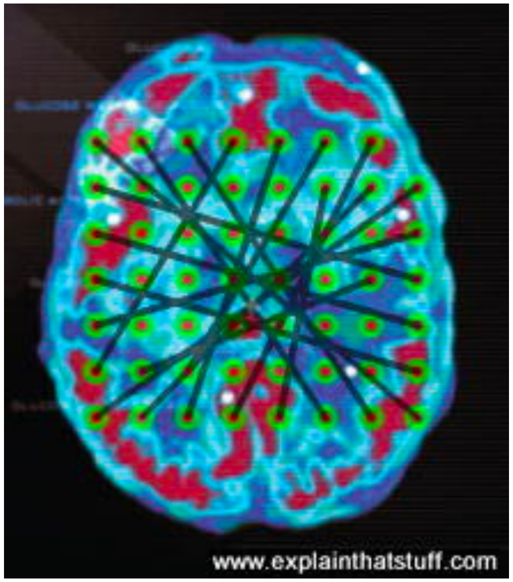
Side note on identifying best parameter weights

- One of the impressive features of ML is how this search is done
- How does ML go about improving (learning) a model?
  - Think about how you climb a steep mountain
  - Calculus does the exact same thing
  - ML does calculus really fast and very frequently

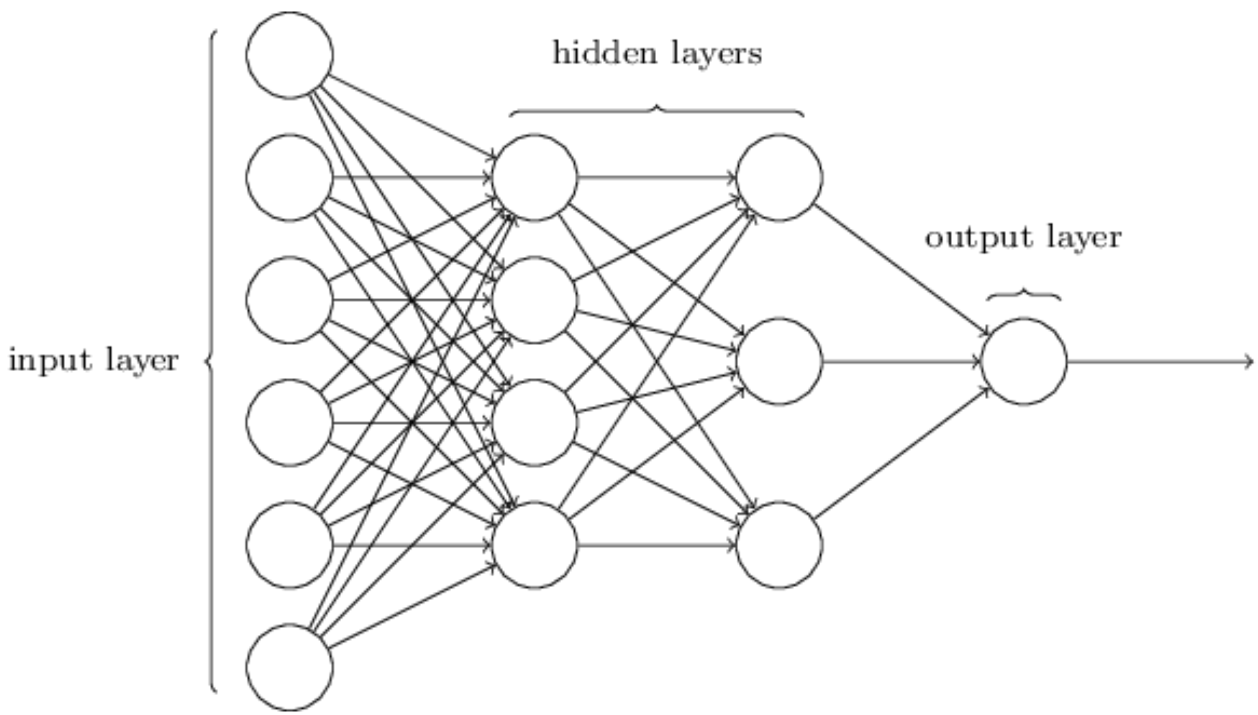
Step 4 – Using Model

Neural networks – how the brain works

- Each neuron receives inputs from other neurons
  - A few neurons also connect to receptors
- The effect of each input line on the neuron is controlled by a synaptic weight
- The synaptic weights adapt so that the whole network learns to perform useful computations
  - Recognizing objects, making plans
- You have about 10^11 neurons each with about 10^14 weights.



Demystifying a neural network



Neural Network Video

Neural network – learn by example

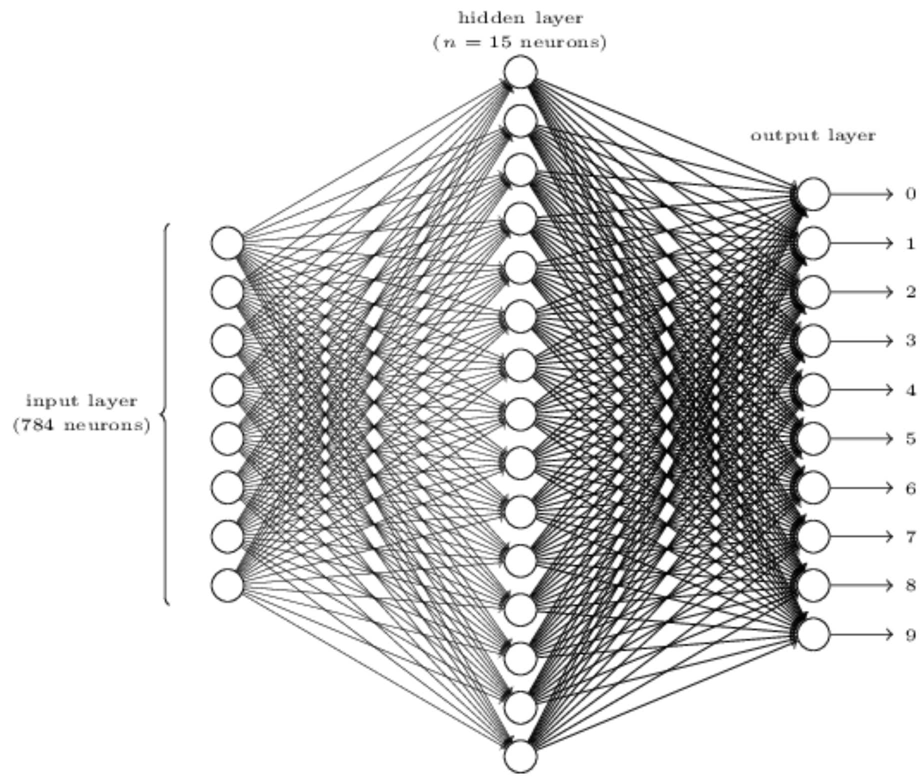
- Popular illustration
  - Handwriting recognition
  - Images available via MNIST

Neural network – learn by example (single digit)

- Start with single digit
- How can we figure out if this 28 x 28 pixel image is a 5?

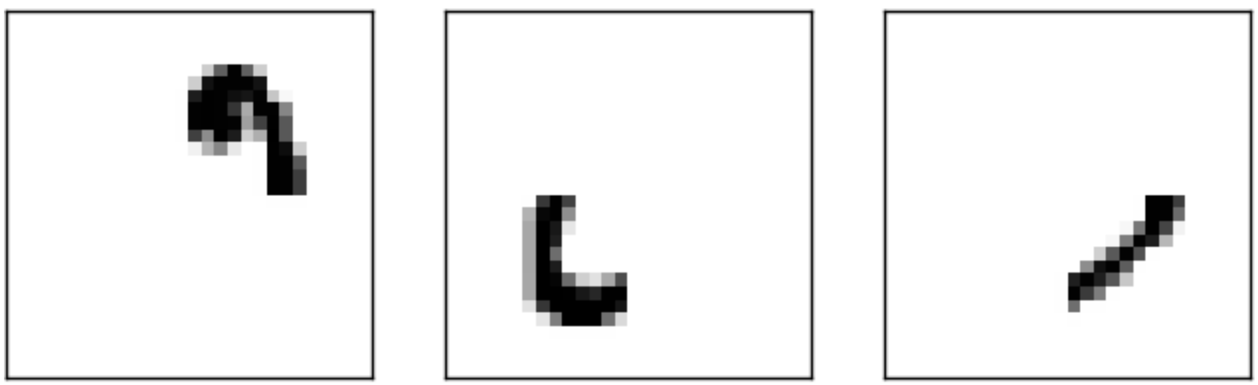
Neural network – learn by example (structure)

- I would argue that this network representation will be all we need.
- Why? Grab a partner and answer the following
  - Why are there 784 neurons in the input layer?
  - Why are there 10 neurons in the output layer?



Neural network – learn by example (hidden layers)

- What are hidden layers?
  - Simple answer: what you want them to be
  - Useful answer: clever components of what you are trying to determine
- I’d argue that the existence of each of the images below might be 3 useful neurons in the hidden layer. Why?



Neural network – learn by example (weights and bias)

- How do we know how 'good' our neural network is at telling us accurate results?
  - I won't get 'mathy', but we really just need a way to see how good/bad our network is performing with specficed weights
  - This will do the trick:

$$C(w, b) \equiv \frac{1}{2n} \sum_x \|y(x) - a\|^2$$

  - C = cost
  - w = weights being used
  - b = biases
  - x = input
    - Input is a 28 x 28 matrix with each value representing the grey value for a particular pixel

CIFAR Demo in MatLAB

- https://cs.stanford.edu/people/karpathy/convnetjs/demo/mnist.html

Using Neural Networks for Retail Forecasting

Item	STORE_NBR	HIST_EVALUATE_START_DT	WM_YR_WK	GREGORIAN_DATE	retail	WKLYQty	Fcst
A	451	1/9/2016	11631	8/27/2016	0.86	1558	
A	5058	12/17/2016	11710	4/1/2017	1.18	1406	
C	1612	2/20/2016	11734	9/16/2017	1.58	1288	
B	1282	10/8/2016	11808	3/17/2018			201.02
C	6469	2/20/2016	11650	1/7/2017	2.97	260	
C	281	2/20/2016	11832	9/1/2018			0
C	2201	2/20/2016	11824	7/7/2018			0
C	1237	2/20/2016	11730	8/19/2017	1.78	565	
B	3357	10/8/2016	11832	9/1/2018			0
A	174	1/9/2016	11625	7/16/2016	0.98	1183	
A	5141	1/9/2016	11641	11/5/2016	1.61	1045	

Step 1 – Data Collection

- Obtain data that can be classified into one of two categories:
    - Information that influences a decision
    - The true outcome of what happened
- In this example, the variables/factors considered in our neural network for each item are:
    - Store number, forecast date, historical forecast date, product, forecast
- The known outcome for each product is:
    - Actual demand

Step 2 – Training, Validation Data Size

- In general, you should divide your data into two parts
  - Data to train your model
  - Data to validate your model
  - 80% training, 20% validation is a reasonable starting place

Step 3 – Determine number of neurons in hidden layer

- For a basic neural network, a good starting place is 10 neurons
- If you are disappointed with the model’s results, this parameter is the first thing to increase and try again
- Remember that the more neurons, the more sophistication and the more computational time

Step 4 – Train your model using input data

- Choose an algorithm to train your neural net with
  - Usually 3 to choose from by default

Step 5 – Assess your results

- Demo output plots

Digging Deeper into Neural Networks

- playground.tensorflow.org

Machine Learning Classification –Example via grocery customer characterization

- So far we have used support vector machines and neural networks to forecast and predict
- There are other useful machine learning functionalities
  - Clustering is one very useful technique for analyzing data
- In clustering, relationships between retail, vendor, customer and product information can reveal trends that lead to improved business strategies
- Scenario:
  - We have sales information for the following categories:
    - Sales Channel, Sales Region, Fresh, Milk, Grocery Frozen, Detergents, Delicatessen

Machine Learning Clustering

- In clustering, there is no prediction to make
  - We only need the categories, not a matching outcome in our data
- We are interested in whether there are quantitative relationships between the categories
  - May reveal customer shopping patterns
  - Could help with replenishment strategies
  - May reveal seasonality and geographic influences on sales

Clustering Video

Step 1 – Data Collection

- Obtain data that has any number of attributes
    - Again, no need for outcome like in prediction/forecasting
- In this example, the categories we will consider are
    - Sales Channel, Sales Region, Fresh, Milk, Grocery Frozen, Detergents, Delicatessen

Step 2 – Self Organizing Model Size

- Determine number of neurons in your model
  - Whatever you choose for # neurons, the clustering map will be # neurons by # neurons
    - 10 is a reasonable starting place

Step 3 – Train your model using input data

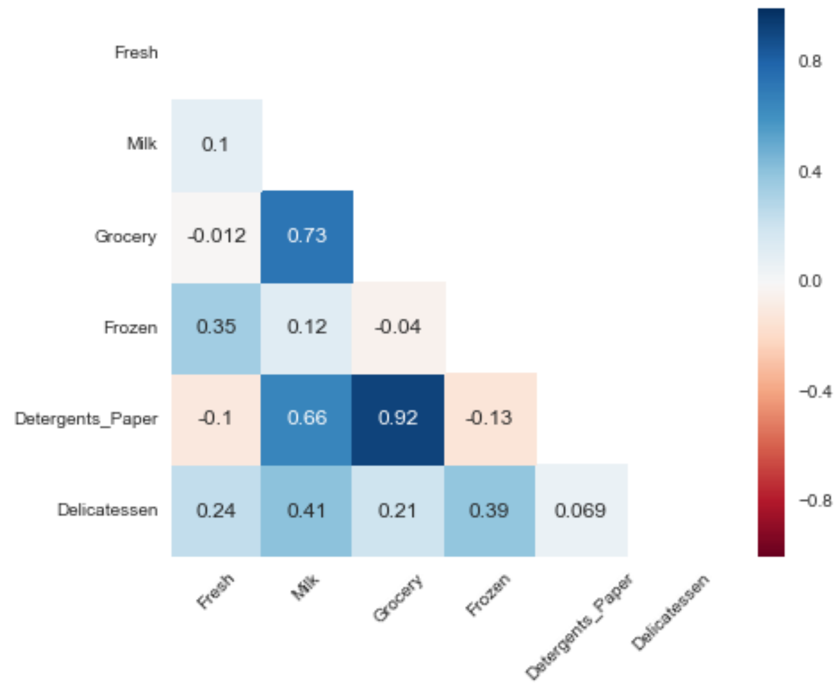
- No models here to choose from

Step 4 – Assess your results

- Demo output plots
- Neighbor weight plots is most telling
  - Indicates divisions in your data

Advanced Data Analysis (Python required)

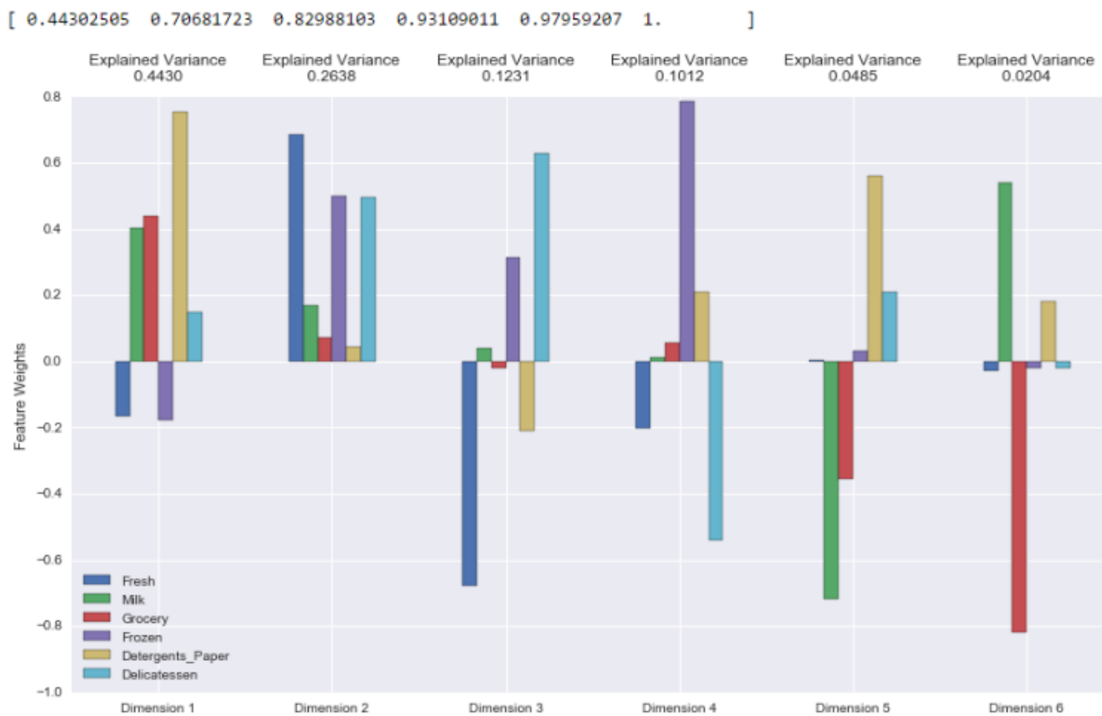
- Pearson co-relation matrix



Advanced Data Analysis (Python required)

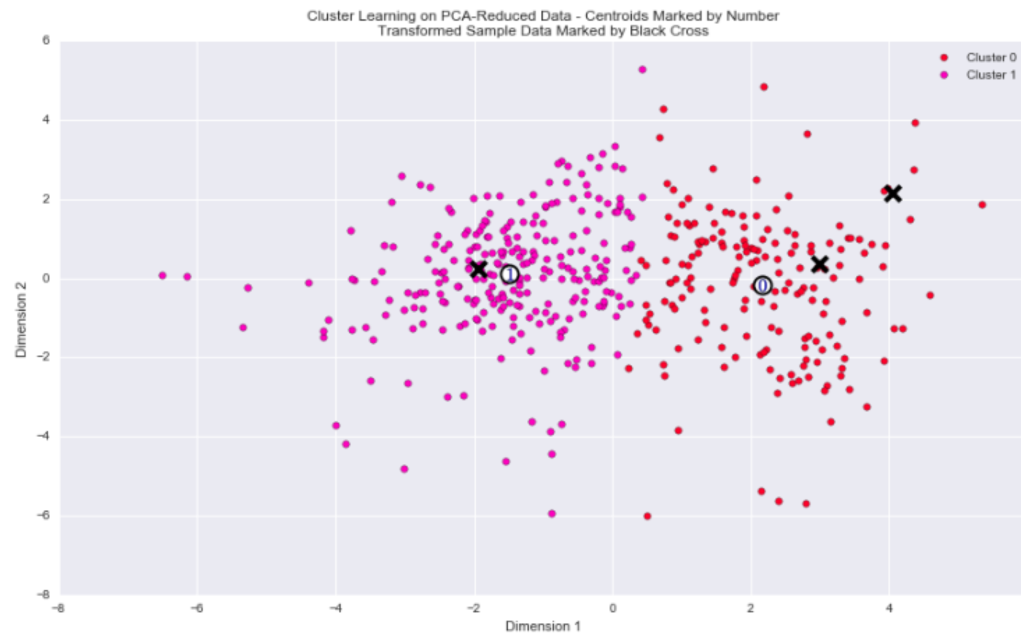
- Principal Component Analysis

Notice how Dimensions 1 and 2 collectively explain variance of all categories well



Advanced Data Analysis (Python required)

- Data is best
grouped into 2 clusters
- Investigating customer
characteristics of these two
clusters show that there
are customers who spend
well below average and
customers who spend slightl
above average



Application of Clustering with Service Counts

invt_event_store_nbr	upc_dept_nbr	upc_nbr	item_unit_retail_amt	in_node_location_id	svc_count	wmt_recount	Unit Price	Item_Tag	Discrepancy_Count	Final Count	Final Adj	Final $ Adj
2821	74	11120234596	249.00	7431	2.00	0.000	249.00	11120234596_7431	0.000	0.000	-2	-498
2821	11	851199001305	159.00	6310	5.00	2.000	159.00	851199001305_6310	2.000	2.000	-3	-477
2821	5	31398267843	34.96	6762	14.00	1.000	34.96	31398267843_6762	1.000	1.000	-13	-454.48
2821	14	75741060088	34.92	7287	14.00	1.000	34.92	75741060088_7287	1.000	1.000	-13	-453.96
2821	92	78742067841	2.48	4870	181.00	0.000	2.48	78742067841_4870	#N/A	0.000	-181	-448.88
2821	4	13700219030	3.48	4700	130.00	8.000	3.48	13700219030_4700	8.000	8.000	-122	-424.56
2821	22	844178033572	21.94	7504	23.00	4.000	21.94	844178033572_7504	4.000	4.000	-19	-416.86
2821	22	815488020682	69.00	4033	12.00	6.000	69.00	815488020682_4033	6.000	6.000	-6	-414
2821	40	854995007007	3.98	53	105.00	1.000	3.98	854995007007_53	#N/A	1.000	-104	-413.92
2821	21	42229272240	5.64	158	144.00	72.000	5.64	42229272240_158	#N/A	72.000	-72	-406.08
2821	5	731855123209	99.96	5	5.00	1.000	99.96	731855123209_5	#N/A	1.000	-4	-399.84
2821	14	887878004527	17.97	7321	26.00	4.000	17.97	887878004527_7321	4.000	4.000	-22	-395.34
2821	87	660543373506	29.92	6914	14.00	1.000	29.92	660543373506_6914	1.000	1.000	-13	-388.96

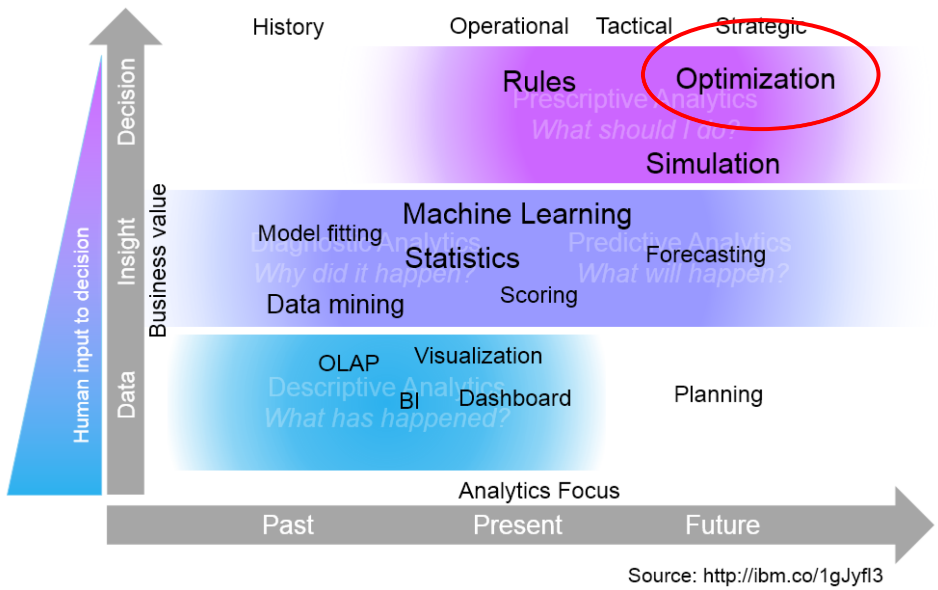
Machine learning clustering could tell us if there are clusters of products that should be recounted?

Is it product location in store

Is it type of product?

Not all decision problems require AI

- I'll even go as far as saying all decision problems don't need AI



Optimization as a Problem Solving Tool

1. Define the problem.
   - what is the problem?
   - who is the decision-maker?
   - select the inputs
     - parameters – beyond the decision-maker's control
       - need data and/or experts to quantify these
     - decision variables – the variables the decision-maker controls
   - we cannot model the entire world
     - we have to leave things out
     - tradeoff between validity and tractability (solvability)

Optimization as a Problem Solving Tool

2. Identify constraints on the decision variables.
    - what limitations are placed on the decision variables?
    - describe these limitations mathematically
3. Identify the objective function(s).
    - what criteria are used to evaluate the quality of solutions?
    - describe these criteria mathematically

Optimization as a Problem Solving Tool

4. Identify a recommended solution.
    - the approach depends on the first three steps

Types of Optimization Models

- deterministic models
  - all parameters are known with certainty
  - goal is typically to find the best solution
- probabilistic models
  - at least one parameter is uncertain (random)
  - goal is typically to develop a method for evaluating solutions one at a time

Example with No Math

1. ranking college football teams

Ranking College Football Teams

- problem (in words)
  - 120 teams
  - each team only plays 8-12 other teams
  - inconsistency in results
    - Team A defeated Team B
    - Team B defeated Team C
    - Team C defeated Team A
  - need to rank the teams from best to worst
    - approximately 7×10^{198} possible rankings

Ranking College Football Teams

- parameters
  - winner and loser of each game
- decision variables
  - where to rank each team
- constraints
  - each team gets one ranking position
  - each ranking position gets one team

Ranking College Football Teams

- objective function
  - minimize the number of violations of individual game results
    - violation $\equiv$ winner ranked below loser

Optimization in Retail Operations

- Items in backroom sit ready for restocking
- A finite number of workers are available for restocking
- In what order should items be restocked so maximize the time usage of the workers?
- This is a very well known optimization problem (traveling salesperson proble) solved for years in other fields:
  - Package delivery
  - Airline routing
- Mathematical programming required, not artificial intelligence

Reshelving Formulation

P : Find $x_{i,j} \in \mathbf{Z}$, $i, j \in \{0, 1, \ldots, n-1\}, i \neq j$, minimizing $\sum d_{i,j} x_{i,j}$ and satisfying

$$
\begin{aligned}
x_{i,j} &\geq 0 \quad \forall i, j \\
x_{i,j} &\leq 1 \quad \forall i, j \\
\textstyle\sum_{j \neq i} x_{i,j} &= 1 \quad \forall i \\
\textstyle\sum_{j \neq i} x_{j,i} &= 1 \quad \forall i
\end{aligned}
$$

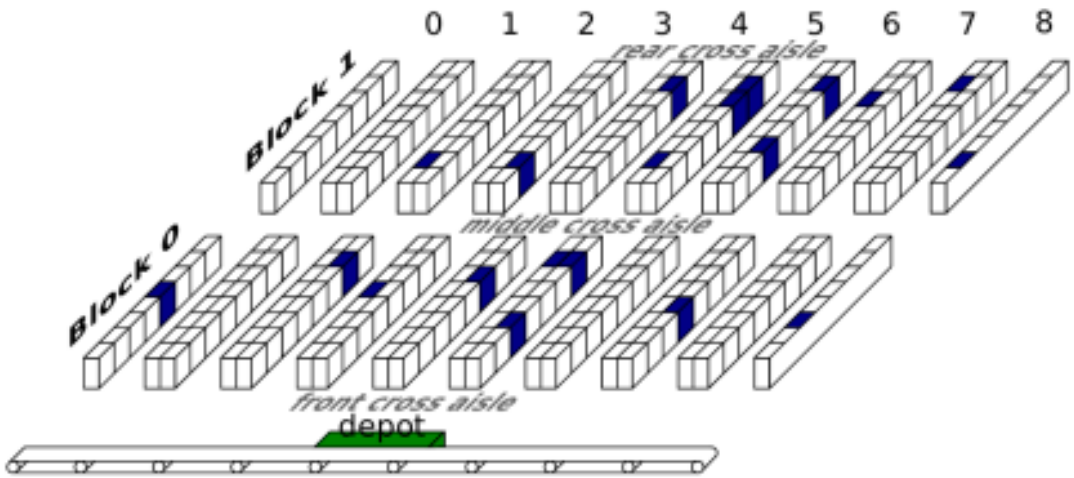
x_i,j is 1 if the worker goes from shelf i to j and 0 otherwise
Constraints 3 and 4 ensure that each shelf is restocked exactly once
d_ij x_ij allows us to keep track of the distance traveled by the worker in a particular solution

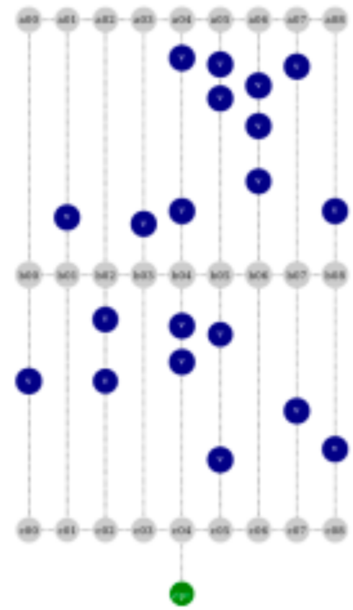
Techniques for Solving Optimization Problems

- Linear programming
- Integer programming
- Heuristics
  - Genetic algorithm
  - Simulated annealing
  - Tabu search
- Not absolutely necessary to be an expert in any one of these. Optimization software will give you solver options. You just need to define objective, decisions and constraints.
- Common optimization solvers: Excel, MatLab, CPLEX, Gurobi, OpenSolver

Restocking Demo

Machine learning – facility operation example





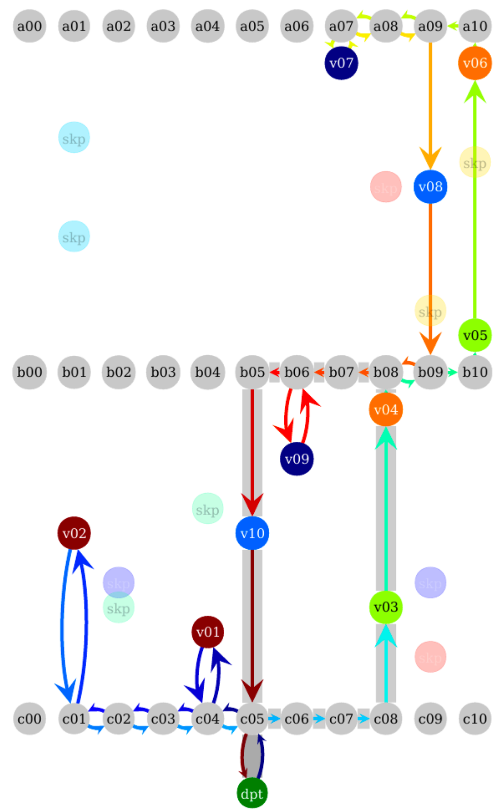
Consider a warehouse control situation with the layout above.

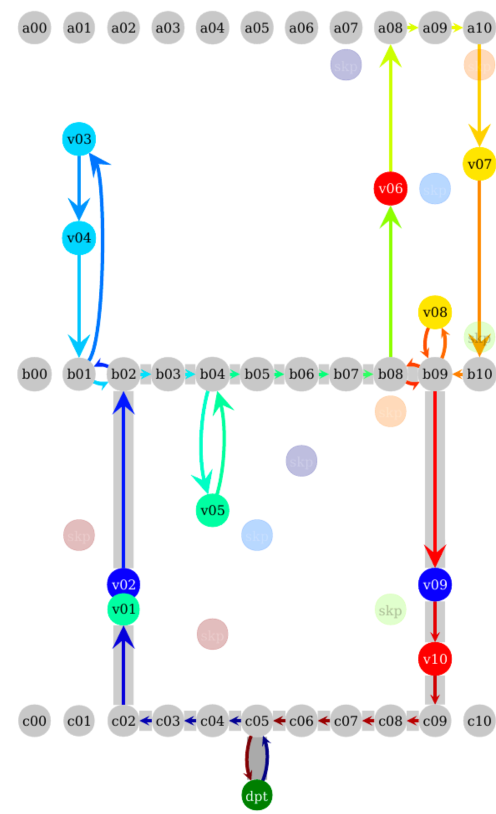
How might AI/ML help in this very common situation?

Credit: Zalando and Nvidia

Facility operations – role of AI/ML

- One realistic application is determining a pick list for a warehouse.





Facility operations – traditional picking

- Identify splits of orders into potential pick lists
- Use known Optimal Cart Pick algorithm calculate travel time for candidate lists
- Optimize these two decisions using genetic algorithm or simulated annealing
- What is the problem?
  - The travel time algorithm takes a few seconds to complete
    - Not feasible to consider a real-size problem
  - Many traditional decision-making approaches are limited to either
    - (i) toy problems that aren't realistic
    - Have no memory property

Facility operations – AI/ML mindset

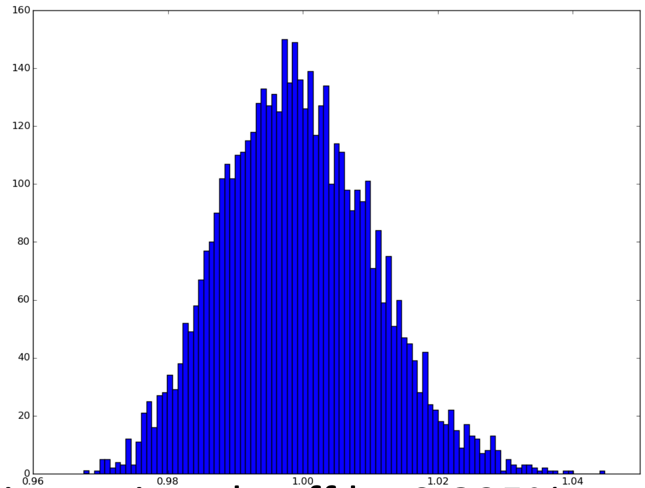
- If we had a better way to determine something as simple as travel time along a route in a warehouse, we could make very powerful decisions
  - What if we didn't calculate travel time from scratch?
  - What if a computer 'knew' the travel time for a potential pick list?
- Given that I'm now telling you that we can use AI/ML to determine common things such as operation times, how do you think we can go about that? Take a few minutes to think about the following:
  - What data do we need?
  - What will be the input/output of our AI/ML model?

Facility operations – AI/ML approach

- Generated millions of random pick lists
- Use travel time algorithm to give each list a “label”: the calculated travel time
- Input the coordinates of the pick lists along with the travel times into a convolutional neural network.
- Train network using Caffe neural network framework
- Final very accurate model determined on the order of weeks

Facility operations – AI/ML solution

- The network estimation of travel times is off by an average of 32.25 seconds for every hour of calculated travel time



- The neural network estimate is only off by 0.895% on average.

Tools to implement AI in business

- Google Cloud Platform
- TensorFlow
- R
- Matlab
- Cray
- Microsoft Azure
- Apache Spark MLlib
- Caffe

AI/ML in Walmart Retail – Interactive Discussion

- What could we do with produce availability information?

Produce Availability Report Walmart

Last Updated: 2017/11/23 02:32:38

New Today

Item Desc	Location	Issue	Store Actions	Anticipated Recovery
APL CHOC PECAN 1PK	3699,4867,6042,6047,6050,6055,6056,6057,6059,6062,6064,6065,6071,6072,6073,6074,6077,6082,6083,6084,6085,6090,6091,6095,6096,6097,6099,6858,7010,7012,7013,7014,7015,7016,7017,7018,7019,7021,7023,7024,7030,7048,7055,7077,7079,7084,7095,7980	Non modular item. Seasonally relevent and delicious.	Place item in refrigerated section with high traffic. Excellent value against competition for a gourmet item.	2017 WEEK 47
APL TRIPLE CHOC 1PK	3699,4867,6042,6047,6050,6055,6056,6057,6059,6062,6064,6065,6071,6072,6073,6074,6077,6082,6083,6084,6085,6090,6091,6095,6096,6097,6099,6858,7010,7012,7013,7014,7015,7016,7017,7018,7019,7021,7023,7024,7030,7048,7055,7077,7079,7084,7095,7980	Non modular item. Feature on refrigeration in high traffic area.	Place item in refrigerated section with high traffic. Excellent value against competition for a gourmet item.	2017 WEEK 47
APPLE AMBROSIA 2# HM	3699,4867,6042,6047,6050,6055,6056,6057,6059,6062,6064,6065,6071,6072,6073,6074,6077,6082,6083,6084,6085,6090,6091,6095,6096,6097,6099,6858,7010,7012,7013,7014,7015,7016,7017,7018,7019,7021,7023,7024,7030,7048,7055,7077,7079,7084,7095,7980	Item not on modular but is the replacement for the season ended Sweetango Bag.	Please utilize Ambrosia 2lb pouch bag to fill the season ending Sweetango 2lb bag.	2018 WEEK 44
APPLE AMBROSIA BULK	3699,4867,6042,6047,6050,6055,6056,6057,6059,6062,6064,6065,6071,6072,6073,6074,6077,6082,6083,6084,6085,6090,6091,6095,6096,6097,6099,6858,7010,7012,7013,7014,7015,7016,7017,7018,7019,7021,7023,7024,7030,7048,7055,7077,7079,7084,7095,7980	Item is not on modular and is the replacement for the season ending Sweetango Bulk.	Please fill the modular home for Sweetango bulk with the Ambrosia Bulk item.	2017 WEEK 49

AI/ML in Walmart Retail – Interactive Discussion

- What could we do with lost sales information?

Store_nbr	OPEN_DATE	STORE_COMP_IND	FINANCIAL_RPT_CODE	STORE_COMP_DESC	RetailerWeek	Act_Sales_Qty	Lost_Sales_	OSCA
1	7/2/62	Y	SC	COMP STORE	201701	312660	14166.83	95.67%
2	8/1/64	Y	SC	COMP STORE	201701	328336	12340.26	96.38%
3	4/12/88	Y	SC	COMP STORE	201701	226279	9275.75	96.06%
4	8/1/65	Y	SC	COMP STORE	201701	292652	11599.09	96.19%
5	5/1/72	Y	SC	COMP STORE	201701	242201	10280.44	95.93%
7	10/1/67	Y	SC	COMP STORE	201701	232378	8943.163	96.29%
8	10/1/67	Y	SC	COMP STORE	201701	170077	5594.263	96.82%
9	3/1/68	Y	SC	COMP STORE	201701	227901	8153.257	96.55%
10	7/30/68	Y	SC	COMP STORE	201701	309625	11868.28	96.31%
11	3/1/68	Y	SC	COMP STORE	201701	386381	16638.66	95.87%
12	7/1/68	Y	SC	COMP STORE	201701	291709	11947.14	96.07%
13	11/1/68	Y	SC	COMP STORE	201701	230522	7902.024	96.69%
14	4/1/69	Y	SC	COMP STORE	201701	296804	11663.39	96.22%
15	5/6/69	Y	SC	COMP STORE	201701	290627	10633.17	96.47%
16	4/1/69	Y	SC	COMP STORE	201701	281067	8878.843	96.94%
17	5/1/69	Y	SC	COMP STORE	201701	296804	10682.34	96.53%
18	11/1/69	Y	SC	COMP STORE	201701	121318	2987.202	97.60%
19	4/3/90	Y	SC	COMP STORE	201701	281626	11672.55	96.02%
20	10/1/70	Y	SC	COMP STORE	201701	188404	6571.858	96.63%
21	3/1/70	Y	SC	COMP STORE	201701	261915	9789.86	96.40%
22	10/1/70	Y	SC	COMP STORE	201701	219982	6793.896	97.00%
23	11/1/70	Y	SC	COMP STORE	201701	227497	7422.031	96.84%
24	4/1/71	Y	SC	COMP STORE	201701	208808	7219.405	96.66%

Words of Caution – AI/ML

- Moving decisions to machines means that securing computers is even more vital
- Machine learning should be viewed as a supplement
- The ‘junk in’ = ’junk out’ philosophy is amplified with AI/ML
- Viewing AI/ML as a black box solution tool is dangerous
- AI/ML is fascinating, but it is not rocket science
  - Many of the concepts coming becoming a reality today were in place many years ago…computational gains and ingenuity by results-focused people are the reason we are talking about these concepts today

The role of AI/ML in retail today

- Most companies are focused (perhaps rightfully so) on using AI/ML to do the following
  - Anticipate customer behavior
  - Change customer behavior
  - Ease the customer experience
- Why this focus?
  - Tunnel vision on data sources
    - Mobile app, internet data and social media drives a huge portion of AI efforts
  - Copycat reality
    - Hard to ignore the advancements in vision and speech recognition in transportation and home use and not incorporate these tools in all industries

AI/ML Opportunities in Retail

- We have yet to give sufficient attention to how ML/AI can assist us with tasks and decisions we’ve been doing for years
- Any answer that 10 years ago was made using a ‘rule of thumb’, and 3 years ago suddenly needed to be data-driven, is a fantastic candidate for ML/AI

Final thoughts and contacting Me

- I’m currently heavily involved in how ML/AI can reshape transportation logistics and would love to have a similar impact in retail
- The first step to appreciating ML/AI is to pilot a project
  - Learning about what ML/AI can’t do is equally beneficial to an initial success

- Email – cer@uark.edu
- Cell – 352-281-7617

Deep Learning Demo

- https://cs.stanford.edu/people/karpathy/convnetjs/demo/rldemo.html