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A Bayesian non-Linear Method for Feature Selection in Machine Translation Quality Estimation

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Abstract We perform a systematic analysis on the effectiveness of features for the problem of predicting the quality of machine translation at the sentence-level. Starting from a comprehensive feature set, we apply a technique based on Gaussian Processes, a Bayesian non-linear learning method, to identify features that perform well on datasets for different language pairs and text domains, with translations produced by various machine translation systems and scored for quality according to different criteria. We show that selecting features with this technique leads to significantly better performance in most datasets, as compared to using the complete feature sets or a state of the art feature selection approach. In addition, we identify a small set of features which seem to perform well across most datasets.

1 Introduction

Machine Translation (MT) systems have been increasingly adopted in recent years for different purposes, including gisting and aiding humans to produce professional quality translations. Since the quality of automatic translations tends to vary significantly across text segments, methods to predict translation quality become more and more relevant. This problem is referred to as Quality Estimation (QE). Different from standard MT evaluation metrics, QE metrics do not have access to reference (human) translations; they are aimed at MT systems in use. Applications of QE include:

- Decide which segments need revision by a human translator;
- Decide whether a reader gets a reliable gist of the text;
- Estimate how much effort it will be needed to post-edit a segment;

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– Select among alternative translations produced by different MT systems.

Work in QE started with the goal of estimating automatic metrics such as BLEU [**?**] and WER [**?**]. However, these metrics are difficult to interpret, particularly at the sentence-level, and results proved unsuccessful. A new surge of interest in the field started recently, motivated by the widespread use of MT systems in the translation industry, as a consequence of better translation quality, more user-friendly tools, and higher demand for translation. In order to make MT maximally useful in this scenario, a quantification of the quality of translated segments similar to "fuzzy match scores" from translation memory systems is needed. QE work addresses this problem by using more complex metrics that go beyond matching the source segment against previously translated data. QE can also be useful for end-users reading translations for gisting, particularly those who cannot read the source language. Recent work focuses on estimating more interpretable metrics, where "quality" is defined according to the task at hand: post-editing, gisting, etc. A number of positive results have been reported (Section 2).

QE is generally addressed as a supervised machine learning task using algorithms to induce models from examples of translations described through a number of **features** and annotated for quality. One of most challenging aspects of the task is the design of feature extractors to capture relevant aspects of quality.

A wide range of features from source and translation texts and external resources and tools have been used. These go from simple, language-independent features, to advanced, linguistically motivated features. They include features that rely on information from the MT system that generated the translations, and features that are oblivious to the way translations were produced. This variety of features plays a key role in QE, but it also introduces a few challenges. Datasets for QE are usually small because of the cost of human annotation. Therefore, large feature sets bring sparsity issues. In addition, some of these features are more costly to extract as they depend on external resources or require time-consuming computations. Finally, it is generally believed that different datasets (i.e. language pair, MT system or specific quality annotation such as post-editing time vs translation adequacy) can benefit from different features.

Feature selection techniques can help not only select the best features for a given dataset, but also understand which features are in general effective. While recent work has exploited selection techniques to some extent, the focus has been on improving QE performance on individual datasets (Section 2). As a result, no general conclusions can be made about the effectiveness of features across language pairs, text domains, MT systems and quality labels.

In this paper we propose to use Gaussian Processes for feature selection, a technique that has proven effective in ranking features according to their discriminative power [**?**]. We benchmark with this technique on two settings: (i) 13 datasets for four language pairs, various Statistical MT (SMT) and rule-based MT (RBMT) systems and four types of quality scores with the same feature sets; (i) one dataset (same language pair and quality scores) with seven feature sets produced in a completely independent fashion (by participants in a shared task on the topic) (Section 4). The experiments showed the potential of feature selection to improve overall regression results, often outperforming published results even on feature sets that had already been previously selected using other methods. They also allowed us to identify a small number of well-performing features across datasets (Section 5). We discuss the feasibility of extracting these features based on their dependence on external resources or specific languages.

2 Related work

Examples of successful cases of QE include improving post-editing efficiency by filtering out low quality segments which would require more effort or time to correct than translating from scratch [**?**,**?**], selecting high quality segments to be published as they are, without post-editing [**?**], selecting a translation from either an MT system or a translation memory for post-editing [**?**], selecting the best translation from multiple MT systems [**?**], and highlighting sub-segments that need revision [**?**]. For an overview of various algorithms and features we refer the reader to the WMT12-13 shared tasks on QE [**?**,**?**].

Most previous work on QE use machine learning algorithms such as Support Vector Machines (SVM), which are robust to redundant/noisy features to a certain extent, and therefore feature selection is often neglected. Work using explicit feature selection methods rely mostly on forward/backward selection approaches, but the order in which features are added/removed is not informed by any prior knowledge. In what follows we summarise recent work using explicit feature selection methods.

[**?**] performed feature selection on a set of 475 sentence- and sub-sentence level features. Principal Component Analysis and a greedy selection algorithm to iteratively create subsets of increasing size with the best-scoring individual features were exploited. Both selection methods yielded better performance than all features, with greedy selection achieving the best MAE scores with 254 features.

[**?**] reported positive results with a greedy backward selection algorithm that removes 21 poor features from an initial set of 66 features based on error minimisation on a development set.

In an oracle-like experiment, [**?**] use a sequential forward selection method, which starts from an empty set and adds one feature at a time as long as it decreases the model's error, evaluating the performance of the feature subsets on the test set directly. 37 features out of 147 are selected, and these significantly improved the overall performance.

[**?**] tested a few feature selection methods using both greedy stepwise and best first search to select among their 266 features with 10-fold cross-validation on the training set. These resulted in sets of 30-80 features, all outperforming the complete feature set. Correlation-based selection with best first search strategy was reported to perform the best. Conversely, [?] reported no improvements in performance in experiments with several selection methods.

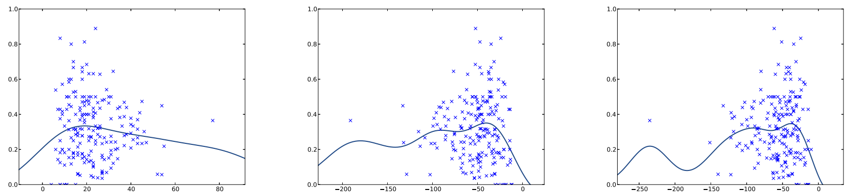
Finally, [?], the winning system in the WMT12 QE shared task, used a computationally-intensive method on a development set. For each of the official evaluation metrics (e.g. MAE), from an initial set of 24 features, all 2^{24} possible combinations were tested, followed by an exhaustive search to find the best combinations. The 15 features belonging to most of the top combinations were selected. Other rounds were added to deal with POS features, but the final feature sets included 14-15 features depending on the evaluation metric. This technique outperformed the complete feature set by a very large margin.

3 Gaussian Processes

Gaussian Processes (GPs; [?]) are an advanced machine learning framework incorporating Bayesian non-parametrics and kernels, and are widely regarded as state of the art for many regression tasks. Despite that, GPs have been under-exploited for language applications. Most of the previous work on QE uses kernel-based Support Vector Machines for regression (SVR), based on experimental findings that non-linear models significantly outperform linear models. This is perhaps unsuprising, given the relatively small numbers of input features used and the complexity of the response variable.

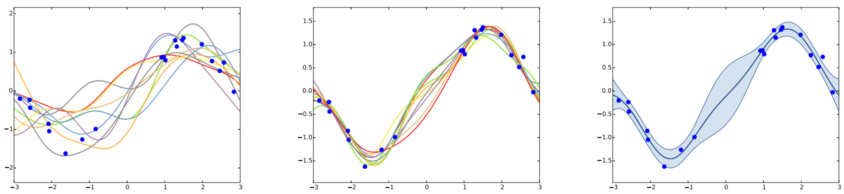
There is little reason to expect that measures of quality, such as post-editing effort, will be a linear function of the input features. To illustrate, consider how quality varies with the length of the source sentence, one of the most important feature in our arsenal. Most short inputs are easy to translate, and therefore we expect the translation quality to be high. In contrast medium length sentences can be much more syntactically complex, leading to much worse translations. However we do not expect that very long sentences are much worse again: in fact they may be simpler, as these sentences are often lists or other highly structured sentences which can be more easily translated. Consequently, positing a linear relationship between input length and quality is not a reasonable proposition. For this feature and many other important features, a non-linear approach is more appropriate. Fig 1 shows three examples of features known to perform very well for translation quality prediction (source sentence length in 1(a), source sentence language model score in 1(b), and target sentence language model score in 1(c)) and their relationship with post-editing distance – HTER [?], with a fitted GP to highlight the non linearity of the data. The same behaviour is observed with other features and other quality labels.

Like SVMs for regression – SVRs, GPs can describe non-linear functions using kernels such as radial basis function (RBF). However in contrast, inference in GP regression can be expressed analytically and the kernel hyper-parameters optimised directly using gradient descent. This avoids the need for costly grid search while also allowing the use of much richer kernel functions with many more parameters. Further differences between the two techniques are that GPs



(a) Length (b) LM source (c) LM target

Fig. 1 Features known to perform well for translation quality prediction (source sentence length in 1(a), source sentence language model score in 1(b), and target sentence language model score in 1(c)) and their relationship with post-editing distance – HTER, with a fitted GP to highlight the non linearity of the data.



(a) posterior samples (b) fitted posterior samples (c) full posterior

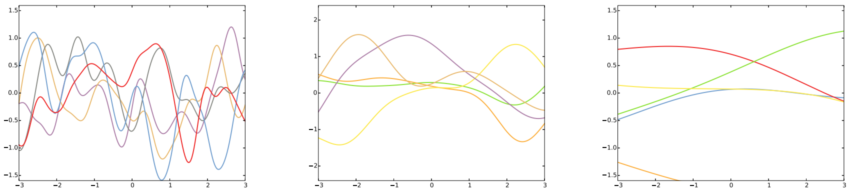
Fig. 2 The Bayesian posterior under a GP prior, illustrated on synthetic one-dimensional data. Figs a and b show samples from the posterior (curves) over functions given several training observations (blue dots). These differ in the values of the hyperparameters, Fig a uses $\sigma_f^2 = \sigma_n^2 = l = 1$, while Fig b has learned the MLE hyper-parameters, $\sigma_f^2 = 0.7, \sigma_n^2 = 0.02, l = 0.3$. Fig c shows the full posterior for the model in b, with the shaded blue error denoting $\pm$ one confidence interval.

are probabilistic models and can be incorporated into larger graphical models. Moreover, GPs take a fully Bayesian approach by integrating out the model parameters to support posterior inference. Unlike most other Bayesian methods, GP regression supports exact posterior inference and learning (see Fig 2), without the need to resort to approximation (e.g., Markov Chain Monte Carlo sampling or variational approximations).

Formulation GP regression assumes the presence of a latent function, $f : \mathbb{R}^F \to \mathbb{R}$, which maps from the input space of feature vectors $\mathbf{x}$ to a scalar. Each response value is then generated from the function evaluated at the corresponding data point, $y_i = f(\mathbf{x}_i) + \eta$, where $\eta \sim \mathcal{N}(0, \sigma_n^2)$ is added white-noise. Formally f is drawn from a GP prior,

$$f(\mathbf{x}) \sim \mathcal{GP}\left(\mathbf{0}, k(\mathbf{x}, \mathbf{x}')\right),$$

which is parameterised by a mean (here, 0) and a covariance kernel function $k(\mathbf{x}, \mathbf{x}')$. The kernel function represents the covariance (i.e., similarities in the response) between pairs of data points. Several draws of f from a GP prior are illustrated in Fig 3.



(a) $l = 0.3$ (b) $l = 1$ (c) $l = 4$

Fig. 3 Samples from a Gaussian Process prior with different length scales in an RBF kernel, showing the effect of this parameter on the smoothness of the function. We consider one dimensional input ($D = 1$), set $\sigma_f = 0.7$ and omit the white-noise term.

Kernel (covariance) function GPs allow for many different kernels. Here we consider the RBF with automatic relevance determination,

$$k(\mathbf{x}, \mathbf{x}') = \sigma_f^2 \exp\left(-\frac{1}{2} \sum_{i}^{D} \frac{(x_i - x_i')^2}{l_i} \right) ,$$

where the $k(\mathbf{x}, \mathbf{x}')$ is the kernel function between two data points $\mathbf{x}$, $\mathbf{x}'$ and D is the number of features, and σ_f and $l_i \geq 0$ are the kernel hyper-parameters, which control the covariance magnitude and the *length scales* of variation in each dimension, respectively. This is closely related to the RBF kernel used with SVR, except that each feature is scaled independently from the others, i.e., $l_i = l$ for SVR, while GPs allow for a vector of independent values. Following standard practice we also include an additive white-noise term in the kernel with variance σ_s^2. The kernel hyper-parameters $(\sigma_f, \sigma_n, \mathbf{l})$ are learned from data using a maximum likelihood estimates.

The learned length scale hyper-parameters can be interpreted as encoding the importance of a feature: the narrower the RBF (the smaller is l_i) the more important a change in the feature value is to the model prediction. This is illustrated in Fig 3, which shows samples from a GP prior with different settings of the length scale: clearly the value of the input will be of less import for Fig 3(c), where the curves are mostly flat, versus Fig 3(a) which allows for rapid fluctuations. This effect can also be seen in the posterior, comparing Figs 2(a) and 2(b), where the latter's shorter length scale allows more accurate fitting of the training points.

Feature selection A model trained using GPs can be viewed as a list of features ranked by relevance, and this information can be used for feature selection by discarding the lowest ranked (least useful) features. GPs on their own do not provide a cut-off point on this ranked list of features, instead this needs to be determined in another way, e.g., by evaluating loss on a separate set to determine the optimal number of features. We experiment with variants on how to determine this cut off point in Section 4.3.

Bayesian inference Given the generative process defined above, prediction can be formulated as Bayesian inference under the posterior,

$$p(y_*|\mathbf{x}_*, \mathcal{D}) = \int_f p(y_*|\mathbf{x}_*, f)p(f|\mathcal{D}),$$

where $\mathbf{x}_*$ is a test input and y_* is its response value. The posterior $p(f|\mathcal{D})$ reflects our updated belief over possible functions after observing the training set $\mathcal{D}$, i.e., f should pass close to the response values for each training instance (but need not fit exactly due to additive noise). This is balanced against the biases (e.g., smoothness constraints) that arise from the GP prior. The posterior is illustrated in Fig 2 (a, b), which shows several samples of f from the posterior in (a,b), which are consistent with the observed training data, $\mathcal{D}$. The predictive posterior can be solved analytically, resulting in

$$y_* \sim \mathcal{N}\big(\mathbf{k}_*^T(K + \sigma_n^2 I)^{-1}\mathbf{y},\ k(\mathbf{x}_*, \mathbf{x}_*) - \mathbf{k}_*^T(K + \sigma_n^2 I)^{-1}\mathbf{k}_*\big), \tag{1}$$

where $\mathbf{k}_* = [k(\mathbf{x}_*, \mathbf{x}_1)\ k(\mathbf{x}_*, \mathbf{x}_2) \cdots k(\mathbf{x}_*, \mathbf{x}_n)]^T$ are the kernel evaluations between the test point and the training set, and $\{K_{ij} = k(\mathbf{x}_i, \mathbf{x}_j)\}$ is the kernel (gram) matrix over the training points. Note that the posterior in Eq. 1 includes not only the expected response (the mean) but also the variance, encoding the model's uncertainty, which is important for integration into subsequent processing, e.g., as part of a larger probabilistic model. The posterior is illustrated in figure 2(c). Note the increasing amounts of uncertainty in the centre of the graph (wider confidence interval) where there are few nearby training instances compared to the edges where there is dense training data. This nuanced modelling of uncertainty is of great importance when combining the model into a larger probabilistic graphical model, such that uncertainty can be preserved into task based inferences.

The remaining question is how to determine the kernel hyperparameters. As stated above, these modulate the effect and strength of the GP prior, in our case determining the relative importance of each feature. The GP framework allows for kernel hyper-parameters to be learned using a maximum likelihood estimate (type II). The marginal likelihood, $p(\mathbf{y}|X) = \int_f p(\mathbf{y}|X, f)p(f)$, can be expressed analytically for GP regression (X are the training inputs), which can be optimised with respect to the hyper-parameters for training (or model selection). Specifically, we can derive the gradient of the (log) marginal likelihood with respect to the model hyperparameters (i.e., $\sigma_n, \sigma_f, \mathbf{l}$ etc.) and thereby find the type II maximum likelihood estimate using gradient ascent. Note that in general the marginal likelihood is non-convex in the hyperparameter values, and consequently the solutions may only be locally optimal. Here we bootstrap the learning of complex models with many hyperparameters by initialising with the (good) solutions found for simpler models, thereby avoiding poor local optima. We refer the reader to [**?**] for further details.

4 Experimental settings

In our experiments, model learning is performed with an open source implementation of `GPs`[1] for regression. This is used for our proposed feature selection method. In what follows we describe two groups of quality estimation datasets: the first group contains various datasets for which we have extracted common feature sets using the QuEst framework [?,?] (Section 4.1); the second group contains a single dataset with various feature sets provided as part of the WMT12 quality estimation shared task (Section 4.2).

4.1 Datasets with QuEst features

The following datasets have a common feature set and are available for download.[2] The statistics of these datasets are shown in Table 1.

WMT12 English-Spanish news sentence translations produced by a phrase-based (PB) Moses "baseline" SMT system,[3] and judged for post-editing effort in 1-5 (highest-lowest), taking a weighted average of three annotators.

EAMT11 English-Spanish (EAMT11-en-es) and French-English (EAMT11-fr-en) news sentence translations produced by a PB-SMT Moses baseline system and judged for post-editing effort in 1-4 (highest-lowest).

EAMT09 English sentences from the European Parliament corpus translated by four SMT systems (two Moses-like PB-SMT systems and two fully discriminative training systems) into Spanish and scored for post-editing effort in 1-4 (highest-lowest). Systems are denoted by s_1-s_4.

GALE11 Arabic newswire sentences translated by two Moses-like PB-SMT systems into English and scored for adequacy in 1-4 (worst-best). Systems are denoted by s_1-s_2.

TRACE English-French (en-fr) and French-English (fr-en) sentence translations produced by two MT systems: a rule-based system (Reverso) and LMSI's statistical MT system [?]. English-French contains a mixture of data from Ted Talks, WMT news, SemEval-2 Cross-Lingual Word Sense Disambiguation, and translation requests from Softissimo's online translation portal (the Reverso system), which can be thought of as user-generated content. The French-English data contains sentences from the OWNI – a free French online newspaper, Ted Talks and translation requests from Softissimo's online translation portal. All translations have been post-edited and the HTER scores are

[1] http://sheffieldml.github.io/GPy/

[2] `http://www.dcs.shef.ac.uk/~lucia/resources.html`

[3] `http://www.statmt.org/moses/?n=Moses.Baseline`

Dataset	Languages	Training	Test
WMT12	en-es	1,832	422
EAMT11	en-es	900	64
EAMT11	fr-en	2,300	225
EAMT09-s_1-s_4	en-es	3,095	906
GALE11-s_1-s_2	ar-en	2,198	387
LIG	fr-en	$9,000$	$1,881$
TRACE	en-fr	$7,599$	$1,323$
TRACE	fr-en	$7,400$	$1,295$
WMT13	en-es	$2,254$	500

Table 1 Number of sentences in our datasets. Figures for EAMT09-s_1-s_4 and GALE11-s_1-s_2 indicate number of sentences per MT system.

used as quality labels. For each language pair, $1,000$ translations have been post-edited by two translators independently. We simply concatenated these in our datasets.

LIG French-English sentence translations of various editions of WMT news test sets, produced by a customised version of a PB-SMT Moses system by the LIG group [?]. These sentences have been post-edited by a human translator, and labelled for HTER.

WMT13 English-Spanish sentence translations of news texts produced by a PB-SMT Moses baseline system. These were then post-edited by a professional translator and labelled for post-editing effort using HTER. This is a superset of the WMT12 dataset, with 500 additional sentences for test, and a different quality label.

4.1.1 Feature sets

The features for these datasets are extracted using the open source toolkit QuEst.[4] We differentiate between *black-box* (BB) and *glass-box* (GB) features, as only BB are available for all datasets (we did not have access to all MT systems that produced the other datasets). For the WMT12 and GALE11 datasets, we experimented with both BB and GB features. The BB feature sets are the same for all datasets, except for the Arabic-English datasets, where language-specific features supplement the initial set of features, and for the WMT13 dataset, where advanced features dependent on external resources like parsers have been exploited.

We also distinguish one special feature: the *pseudo-reference* (PR), as this is not a standard feature in that it requires another MT system to be extracted. This feature consists in translating the source sentence using another MT system (in our case, Google Translate) to obtain a *pseudo-reference*. The geometric mean of (lambda-smoothed) 1-to-4-gram precision scores (i.e. a smoothed

[4] `http://www.quest.dcs.shef.ac.uk`

version of BLEU to avoid 0-counts without the brevity penalty) is then computed between the original MT and this pseudo-reference. We note that the better the external MT system, the closer the pseudo-reference translation is to a human translation, and therefore the more reliable this feature becomes.

For each dataset we built four QE systems, each with a feature set:

- **BL**: 17 features that performed well across languages in previous work and were used as baseline in the WMT12-13 QE shared tasks.
  - number of tokens in the source & target sentences
  - average source token length
  - average number of occurrences of the target word within the target sentence
  - number of punctuation marks in source and target sentences
  - language model (LM) probability of source and target sentences using 3-gram LMs built from the source/target sides of SMT training corpus
  - average number of translations per source word as given by IBM 1 model thresholded such that $P(t|s) > 0.2$
  - same as above with $P(t|s) > 0.01$ weighted by the inverse frequency of each word in the source side of the SMT training corpus
  - percentage of unigrams, bigrams and trigrams in frequency quartiles 1 (lower frequency words) and 4 (higher frequency words) in the source side of the SMT training corpus
  - percentage of unigrams in the source sentence seen in the source side of the SMT training corpus
- **AF**: All features available for the dataset. This is a superset of the above, where:
  - For the experiments with BB features we have a common set of 80 features for all datasets, and additional 43 language specific features for the Arabic-English datasets, or additional advanced features for the WMT13 dataset, for which resources had been previously curated.
  - For the experiments with GB features we have all MT system-dependent features (varying according to the actual type of MT system) available for the GALE11-s_1 (39), GALE11-s_2 (48), and WMT12 (47) datasets.

  For a comprehensive list, we refer the reader to the QuEst project website.[4]
- **BL+PR**: 17 baseline features along with a pseudo reference feature.
- **AF+PR**: All features available (BB, GB or BB+GB) plus the pseudo-reference feature.

4.2 WMT12 datasets

This is exactly the same as the WMT12 dataset described above. However, as feature sets, we use those provided by all but one of the participating teams in the WMT12 shared task on QE.[5] These very diverse feature sets, with

[5] These feature sets were made available by the task organisers at `http://www.dcs.shef.ac.uk/~lucia/resources.html`

features of many different natures, although some overlap with the QuEst features exists in most cases. We denote each of these feature set **AF**. We note however that in a few cases these are only a subset of the features actually used in the shared task, e.g. **UU**, since the participants could not provide us with the full feature sets. This explains the difference between the official scores reported in [?] and our figures. This difference can also be explained by the learning algorithms: while we used `GPs`, participants have used SVRs, M5P and other algorithms. Some of these feature sets already result from feature selection techniques.

SDL [?]: 15 features selected after an exhaustive search algorithm based on all possible combinations of features. This is the optimal set used by the winning submission. It includes many of the baseline features, the pseudo-reference feature, phrase table probabilities, and a few part-of-speech tag alignment features.

UU [?]: 82 features, a subset of those used in the shared-task as the parse tree features (based on tree-kernels) were not provided by the participants. These are similar to the common BL and BB features presented above and include various source and target LM features, average number of translations per source word, number of tokens matching certain patterns (hyphens, ellipsis, etc.), percentage of n-grams seen in corpus, percentage of non-aligned words, etc.

UEdin [?]: 56 black-box features including source translatability, named entities, LM back-off features, discriminative word-lexicon, edit distance between source sentence and the SMT source training corpus, and word-level features based on neural networks to select a subset of relevant words among all words in the corpus.

Loria [?]: 49 features including 1-5gram LM and back-off LM features, interlingual and cross-lingual mutual information features, IBM1 model average translation probability, punctuation checks, and out-of-vocabulary rate.

TCD [?]: 43 features based on the similarity between the (source or target) sentence and a reference set (the SMT training corpus or Google N-grams) with n-grams of different lengths, including the TF-IDF metric.

WLV-SHEF [?]: 147 features which are a superset of the common 80 black-box features above. The additional features include a number of linguistically motivated features for source or target sentences (percentage) or their comparison (ratio), such as content words and function words, width and depth of constituency and dependency trees, nouns, verbs and pronouns.

UPC [**?**]: 56 features on top of the baseline features. Most of these features are based on different language models estimated on reference and automatic Spanish translations.

4.3 Feature selection techniques

As previously described, our proposed technique for feature selection uses `GPs`. In each dataset, features are first normalised. Each feature is centred and scaled to have zero mean and unit standard deviation. For feature ranking, the models are trained on the full training sets, except in the **FS(GP-dev)** setting (below). The RBF widths, scale and noise variance are initialised with an isotropic kernel (with a single length scale, $l_i = l$) which helps to avoid local minima. We apply a sparse approximation method for inference, known as FITC (Fully Independent Training Conditional), which bases parameter learning on a few inducing points in the training set instead of the entire training set. This approximation technique is used to make the learning less computationally expensive and therefore faster, which is important for large training sets. The hyper-parameters are learned using gradient descent with a maximum of 100 iterations and cross-validation on the training set. A forward selection approach is then used to select features ranked from top to worst and train models using `GPs` with increasing numbers of features and all available training data.

Four variant of selection techniques were used in our experiments, all applied on the entire set of features (**AF+PR** for the QuEst datasets, and **AF** for the WMT12 datasets):

- **FS(GP-dev)**: Feature selection on **AF+PR** for automatic ranking and selection of top features with `GPs` on a development set and applied to test set.
- **FS(GP-fixed)**: Feature selection on **AF+PR** for automatic ranking and selection of top features with `GPs` and a fixed number of features (threshold pre-
- **FS(GP-test)**: Feature selection on **AF+PR** for automatic ranking and selection of top features with `GPs` directly on test set (oracle selection).
- **FS(RL)**: Feature selection with Randomized Lasso.

In **FS(GP-dev)**, a development set is randomly selected from the training data for each of the dataset. In each of the datasets, we extracted the same number of sentences for development as there were for the test set. The development set was then used to choose the cutoff point in the ranked set of features generated by the `GP` model, i.e., where to stop selecting features. Once we performed feature selection over development set, the full training set was used to train the final models.

FS(GP-fixed) is based on pre-defined threshold on number of features to select for model training. The threshold was decided empirically based on previous experiments on various datasets. We observed that the optimal number of features oscillates between 10 and 30 features for different datasets. In these experiments, we selected 17 as fixed threshold for two reasons: it falls within this range and it allows for an interesting comparison with the intuitively selected 17 baseline features.

In **FS(GP-test)**, the selected set is evaluated under an oracle condition, where the optimal number of features is decided based on the best performance obtained directly on the test set. This experiment aimed to study the upper bound in performance of the `GPs`-based method for feature selection. The subset of top ranked features that minimises error in each test set is selected.

As an alternative approach to `GPs`, we use Randomized Lasso, **FS(RL)**, for feature selection. Randomised Lasso repeatedly resamples the training data and fits a Lasso regression model on each sample. A feature is selected for the final model if it is selected (i.e., assigned a non-zero weight) in at least 25% of the samples (we do this 1000 times). This strategy improves the robustness of Lasso in the presence of high dimensional and correlated inputs. It should be noted that **FS(RL)** automatically selects the number of features to be used for training. The final models are still trained using `GPs` on the selected features.

4.4 Evaluation metrics

To evaluate the prediction models we use Mean Absolute Error (MAE), its squared version – Root Mean Squared Error (RMSE), plus the Relative Absolute Error (RAE) and its squared version – Relative Squared Error (RSE). MAE is used as the main metric on the charts for a comparative analysis. RAE provides the average error relative to a simple predictor, which is just the average of the true values. It is meant to provide some form of comparison across prediction models for different datasets.

$$\text{MAE} = \frac{\sum_{i=1}^{N} |H(s_i) - V(s_i)|}{N} \qquad \text{RMSE} = \sqrt{\frac{\sum_{i=1}^{N} (H(s_i) - V(s_i))^2}{N}}$$

$$\text{RAE} = \frac{\displaystyle\sum_{i=1}^{n} |H(s_i) - V(s_i)|}{\displaystyle\sum_{i=1}^{n} |\bar{V}(s) - V(s_i)|} \qquad \text{RSE} = \sqrt{\frac{\displaystyle\sum_{i=1}^{n} (H(s_i) - V(s_i))^2}{\displaystyle\sum_{i=1}^{n} (\bar{V}(s) - V(s_i))^2}}$$

where:
$N = |S|$ is the number of test instances,
$H(s_i)$ is the predicted score for s_i,
$V(s_i)$ is the true (human) score for s_i,
$\bar{V}(s)$ is the mean true score (on the test set).

5 Results

We note that preliminary results for some of the datasets used here have been reported in [**?**]. The following results include additional datasets and further analysis.

5.1 Results on QuEst feature sets

The error scores for all datasets with common (QuEst) black-box (BB) features are reported in Tables 2 and 3, while Table 4 shows the results with glass-box (GB) features for a subset of these datasets, and Table 5 the results with BB and GB features together for the latter datasets. For each Table and dataset, bold-faced figures represent results that are significantly better (paired t-test with $p \leq 0.05$) with respect to the following comparisons – where available, while underlined figures represent best results overall and double underlined figures, the second best results:

- BL vs AF;
- BL vs BL+PR;
- AF vs AF+PR; and
- Each feature selection techniques versus AF+PR.

In what follows we take a closer look at some of these comparisons, as well as the difference between different types of feature selection methods. We summarise these comparisons graphically in Fig 4. This figure shows the improvements of different feature sets over the BL results. We also discuss the impact of using GB features against BB features only, showing the improvements of various feature sets over the use of black-box features in Fig 6.

Baseline features vs all feature sets Adding more features (systems **AF**) leads to better results in most cases as compared to the baseline systems **BL**, except for some of the EAMT-09 datasets. However, these are small and in some cases not significant improvements. Adding more features may bring more relevant information, but at the same time it makes the representation more sparse and the learning prone to overfitting. Larger improvements over the baseline come from using either a pseudo-reference feature or performing feature selection, as we discuss in what follows.

Impact of the pseudo-reference feature Adding a single feature, the pseudo-reference (systems **BL+PR**) to our baseline improves results in all datasets, often by a large margin. Similar improvements are observed by adding this feature to the set with all available features (systems **AF+PR**).

Dataset	System	#feats.	MAE	RMSE	RAE	RSE
EAMT11-en-es	Mean	-	0.6027	0.7314	1.0172	1.126
	BL	17	0.4857	0.6178	0.8780	1.2071
	AF	80	**0.4719**	**0.5418**	**0.8709**	**1.1808**
	BL+PR	18	**0.4490**	**0.5329**	**0.8417**	**0.9917**
	AF+PR	81	**0.4471**	**0.5301**	**0.8414**	**0.9905**
	FS(GP-dev)	13	**0.4370**	**0.5199**	**0.8424**	**0.9911**
	FS(GP-fixed)	17	**0.4397**	**0.5224**	**0.8411**	**0.9901**
	FS(GP-test)	20	**0.4320**	**0.5260**	**0.8330**	**0.9861**
	FS(RL)	69	0.4457	0.5324	0.8501	0.9937
EAMT11-fr-en	Mean	-	0.5411	0.6927	1.0813	1.314
	BL	17	0.4401	0.6301	0.9829	1.089
	AF	80	**0.4292**	**0.6222**	**0.9708**	**1.001**
	BL+PR	18	**0.4183**	**0.6213**	**0.9614**	**0.9972**
	AF+PR	81	**0.4169**	**0.6181**	**0.9682**	**0.9913**
	FS(GP-dev)	15	**0.4123**	**0.6021**	**0.9627**	**0.9937**
	FS(GP-fixed)	17	0.4166	0.6176	0.9614	0.9920
	FS(GP-test)	10	**0.4110**	**0.6099**	**0.9387**	**0.9891**
	FS(RL)	65	0.4165	0.6180	0.9553	0.9871
EAMT09-s_1	Mean	-	0.5382	0.7092	1.0392	1.0036
	BL	17	0.5313	0.6655	0.8217	0.8111
	AF	80	**0.5265**	**0.6538**	**0.7949**	**0.7535**
	BL+PR	18	**0.5123**	0 **.6492**	**0.7712**	**0.7423**
	AF+PR	81	**0.5109**	**0.6441**	**0.7467**	**0.7374**
	FS(GP-dev)	16	**0.5055**	**0.6409**	**0.7367**	**0.7166**
	FS(GP-fixed)	17	**0.5045**	**0.6392**	**0.7350**	**0.7175**
	FS(GP-test)	13	**0.5025**	**0.6391**	**0.7317**	**0.7117**
	FS(RL)	73	0.5195	0.6416	0.7401	0.7320
EAMT09-s_2	Mean	-	0.6854	0.7926	1.0060	1.0016
	BL	17	0.4614	0.5816	0.8933	0.7384
	AF	80	0.4741	0.5953	0.8997	0.790
	BL+PR	18	**0.4493**	**0.5692**	**0.8714**	**0.7211**
	AF+PR	81	**0.4609**	**0.5821**	**0.8701**	**0.7188**
	FS(GP-dev)	17	**0.4514**	**0.5735**	**0.8711**	**0.7120**
	FS(GP-fixed)	17	**0.4514**	**0.5735**	**0.8711**	**0.7120**
	FS(GP-test)	12	**0.4410**	**0.5625**	**0.8514**	**0.7013**
	FS(RL)	59	0.4601	0.5807	0.8677	0.7114
EAMT09-s_3	Mean	-	0.6753	0.7751	1.0013	1.0009
	BL	17	0.5339	0.6619	0.8114	0.7628
	AF	80	0.5437	0.6827	0.7949	0.7535
	BL+PR	18	**0.5113**	**0.6492**	**0.7717**	**0.7490**
	AF+PR	81	**0.5309**	**0.6771**	**0.7701**	**0.7489**
	FS(GP-dev)	15	**0.5140**	**0.6591**	**0.7527**	**0.7324**
	FS(GP-fixed)	17	**0.5130**	**0.6572**	**0.7515**	**0.7312**
	FS(GP-test)	15	**0.5060**	**0.6410**	**0.7471**	**0.7250**
	FS(RL)	67	0.5295	0.6727	0.7680	0.7450
EAMT09-s_4	Mean	-	0.49904	0.6112	0.9991	1.0000
	BL	17	0.3591	0.4942	0.7319	0.9759
	AF	80	0.3578	0.4960	0.7335	0.9712
	BL+PR	18	**0.3401**	**0.4811**	**0.7216**	**0.9584**
	AF+PR	81	**0.3409**	**0.4816**	**0.7224**	**0.9591**
	FS(GP-dev)	18	0.3381	0.4814	0.7113	0.9381
	FS(GP-fixed)	17	0.3383	0.4811	0.7101	0.9374
	FS(GP-test)	19	0.3370	0.4799	0.7011	0.9312
	FS(RL)	40	0.3404	0.4805	0.7221	0.9571

Table 2 Results for datasets with common BB features - part 1.

Dataset	System	#feats.	MAE	RMSE	RAE	RSE
WMT12	Mean	-	0.8278	0.9898	1.0247	1.0263
	BL	17	0.6821	0.8117	0.8622	0.7152
	AF	80	**0.6717**	**0.8103**	**0.8476**	**0.6954**
	BL+PR	18	**0.6290**	**0.7729**	**0.8139**	**0.6678**
	AF+PR	81	**0.6324**	**0.7735**	**0.7745**	**0.6699**
	FS(GP-dev)	15	**0.6231**	**0.7658**	**0.7719**	**0.6651**
	FS(GP-fixed)	17	**0.6224**	**0.7645**	**0.7701**	**0.6644**
	FS(GP-test)	19	**0.6131**	**0.7598**	**0.7613**	**0.6586**
	FS(RL)	71	0.6335	0.7724	0.7755	0.6709
WMT13	Mean	-	0.1438	0.1792	1.0036	1.0009
	BL	17	0.1411	0.1812	0.9723	1.086
	AF	114	0.1389	0.1775	0.9211	0.9713
	BL +PR	18	0.1409	0.1802	0.9711	1.063
	AF+PR	115	0.1367	0.1759	0.9181	0.9693
	FS(GP-dev)	19	**0.1217**	**0.1411**	**0.8907**	**0.9577**
	FS(GP-fixed)	17	**0.1242**	**0.1489**	**0.8911**	**0.9581**
	FS(GP-test)	19	**0.1207**	**0.1481**	**0.8844**	**0.9531**
	FS(RL)	101	0.1317	0.1691	0.9201	0.9709
GALE11-s_1	Mean	-	0.5823	0.7214	0.8533	0.8125
	BL	17	0.5462	0.6885	0.8186	0.7715
	AF	123	**0.5399**	**0.6805**	**0.8017**	**0.7619**
	BL+PR	18	**0.5301**	**0.6814**	**0.7929**	**0.7595**
	AF+PR	81	**0.5249**	**0.6766**	**0.7905**	**0.7520**
	FS(GP-dev)	21	0.5220	0.6751	0.7871	0.7581
	FS(GP-fixed)	17	0.5231	0.6761	0.7856	0.7577
	FS(GP-test)	27	0.5210	0.6701	0.7811	0.7434
	FS(RL)	56	0.5258	0.6749	0.7914	0.7530
GALE11-s_2	Mean	-	0.5850	0.7527	0.8573	0.8313
	BL	17	0.5540	0.7117	0.8287	0.7978
	AF	123	**0.5401**	**0.6911**	**0.8232**	**0.7931**
	BL+PR	18	**0.5401**	**0.7014**	**0.8221**	**0.7901**
	AF+PR	81	**0.5249**	**0.6806**	**0.8154**	**0.7892**
	FS(GP-dev)	22	**0.5197**	**0.6769**	**0.8133**	**0.7853**
	FS(GP-fixed)	17	0.5219	0.6794	0.8123	0.7841
	FS(GP-test)	31	**0.5194**	**0.6779**	**0.8081**	**0.7815**
	FS(RL)	54	0.5239	0.6805	0.8134	0.7899
LIG	Mean	-	0.1326	0.1727	.9938	1.0245
	BL	17	0.1250	0.1638	0.9369	0.9223
	AF	80	0.1227	0.1631	0.9344	0.9209
	BL+PR	18	**0.1159**	**0.1527**	**0.9312**	**0.9191**
	AF+PR	81	**0.1161**	**0.1534**	**0.9313**	**0.9183**
	FS(GP-fixed)	17	**0.1087**	**0.1504**	**0.9287**	**0.9135**
	FS(GP-dev)	13	**0.1077**	**0.1493**	**0.9284**	**0.9145**
	FS(GP-test)	13	**0.1054**	**0.1489**	**0.9227**	**0.9099**
	FS(RL)	69	0.1154	0.1519	0.9321	0.9178
TRACE-fr-en	Mean	-	0.1868	0.2470	1.0079	1.0030
	BL	17	0.1807	0.2429	0.9749	0.9695
	AF	80	0.1776	0.2422	0.9678	0.9611
	BL+PR	18	**0.1729**	**0.2210**	**0.9611**	**0.9554**
	AF+PR	81	**0.1687**	**0.2127**	**0.9601**	**0.9521**
	FS(GP-dev)	18	**0.1564**	**0.2081**	**0.9571**	**0.9499**
	FS(GP-fixed)	17	**0.1597**	**0.2101**	**0.9565**	**0.9487**
	FS(GP-test)	19	**0.1554**	**0.2089**	**0.9515**	**0.9421**
	FS(RL)	72	0.1654	0.2109	0.9589	0.9501
TRACE-en-fr	Mean	-	0.1891	0.2460	1.0004	1.0021
	BL	17	0.1782	0.2389	0.9315	0.9354
	AF	80	**0.1657**	**0.2279**	**0.9261**	**0.9292**
	BL+PR	18	**0.1729**	**0.2210**	**0.9292**	**0.9314**
	AF+PR	82	0.1637	0.2127	0.9211	0.9226
	FS(GP-dev)	15	**0.1615**	**0.2133**	**0.9209**	**0.9221**
	FS(GP-fixed)	17	**0.1612**	**0.2127**	**0.9201**	**0.9211**
	FS(GP-test)	18	**0.1611**	**0.2131**	**0.9178**	**0.9193**
	FS(RL)	71	0.1633	0.2241	0.9209	0.9220

Table 3 Results for datasets with common BB features - part 2.

Dataset	System	#features	MAE	RMSE	RAE	RSE
WMT12	AF	47	0.7066	0.8445	0.9114	0.7467
	FS(GP-dev)	19	**0.6789**	**0.8318**	**0.8931**	**0.7210**
	FS(GP-fixed)	17	**0.6775**	**0.8314**	**0.8914**	**0.7196**
	FS(GP-test)	21	**0.6755**	**0.8298**	**0.8814**	**0.7119**
	FS(RL)	35	**0.6921**	**0.8388**	**0.9057**	**0.7411**
GALE11-s$_1$	AF	39	0.5736	0.7402	0.8516	0.8131
	FS(GP-dev)	18	0.5715	0.7385	0.8499	0.8080
	FS(GP-fixed)	17	0.5732	0.7381	0.8491	0.8098
	FS(GP-test)	19	**0.5702**	**0.7361**	**0.8441**	**0.8060**
	FS(RL)	33	0.5781	0.7481	0.8501	0.8111
GALE11-s$_2$	AF	48	0.5540	0.6979	0.8317	0.8060
	FS(GP-dev)	21	**0.5451**	0.6998	**0.8243**	**0.8005**
	FS(GP-fixed)	13	0.5491	0.6944	0.8261	0.8011
	FS(GP-test)	13	**0.5411**	**0.6934**	**0.8220**	**0.8001**
	FS(RL)	41	0.5512	0.6950	0.8301	0.8041

Table 4 Results with GB features.

Dataset	System	#features	MAE	RMSE	RAE	RSE
WMT12	AF	128	0.7185	0.8451	0.9137	0.7507
	FS(GP-dev)	25	**0.6121**	**0.7582**	**0.7692**	**0.6629**
	FS(GP-fixed)	17	**0.6161**	**0.7591**	**0.7703**	**0.6639**
	FS(GP-test)	29	**0.6101**	**0.7561**	**0.7679**	**0.6611**
	FS(RL)	99	**0.6601**	**0.8098**	**0.7815**	**0.6779**
GALE11-s$_1$	AF	163	0.5455	0.6722	0.8226	0.7755
	FS(GP-dev)	27	**0.5162**	**0.6699**	**0.7801**	**0.7411**
	FS(GP-fixed)	17	**0.5170**	**0.6701**	**0.7810**	**0.7421**
	FS(GP-test)	30	**0.5150**	**0.6681**	**0.7785**	**0.7384**
	FS(RL)	132	**0.5310**	**0.6731**	**0.7911**	**0.7501**
GALE11-s$_2$	AF	172	0.5239	0.6529	0.8177	0.7915
	FS(GP-dev)	27	**0.5120**	**0.6441**	**0.8094**	**0.7812**
	FS(GP-fixed)	17	**0.5119**	**0.6451**	**0.8111**	**0.7823**
	FS(GP-test)	17	**0.5109**	**0.6431**	**0.8063**	**0.7795**
	FS(RL)	132	**0.5155**	**0.6499**	**0.8144**	**0.7887**

Table 5 Results with common BB & GB features.

Impact of feature selection Our experiments with feature selection using both `GPs` and `RL` led to significant improvements over the entire set of features. Feature selection with `GPs` has shown better performance over feature selection with `RL`.

For a more comprehensive overview of the results of feature selection using `GPs`, we plot the MAE error scores (on the test sets) for different cut-off points on the features in our forward selection method after features are ranked by `GPs`. The plots for two of our datasets are given in Fig 5. The y axis shows the MAE scores, while the x axis shows the number of features selected. Generally, we observe a very fast error decrease in the beginning as features are added until approximately 20 features, where the minimum (optimal) error scores are found, and as more features are added, the error starts to quickly increase again, until a plateau is reached (approximately 45 features). This shows that

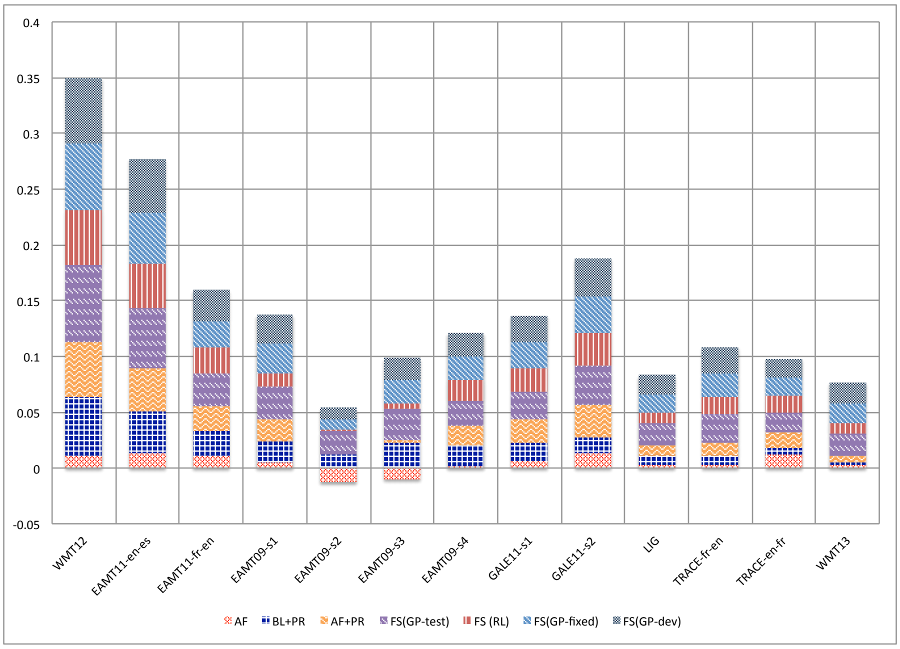


Fig. 4 Improvements of various feature-sets over the BL features. The height of the bar representing a feature set is proportional to the actual improvement it brings over the results with the baseline feature set.

while a very small number of features is naturally insufficient, adding features ranked lower by `GPs` degrades performance. Similar curves were observed for all datasets with slightly different ranges for optimal numbers of features and best score. It is interesting to note that the best performance on most datasets is observed using 10-20 top-ranked features. This explains why **FS(GP-fixed)** performs as well as **FS(GP-dev)** or even **FS(GP-test)**, in most cases. Given that **FS(GP-dev)** and **FS(GP-fixed)** perform equally well in most cases, the choice between them could be guided by the size of the dataset: if enough data is available to put a development set aside, this should be preferable, while **FS(GP-fixed)** should be used as a cheaper alternative approach if necessary.

Black-box versus glass-box features GB features on their own perform worse than BB features (Fig 6), but in all three datasets the combination of GB and BB followed by feature selection resulted in significantly lower error than using only BB features with feature selection, showing that the two features sets are complementary.

5.2 Results on WMT12 datasets

In order to investigate whether our feature selection results hold for other feature sets, we experimented with the feature sets provided by most teams

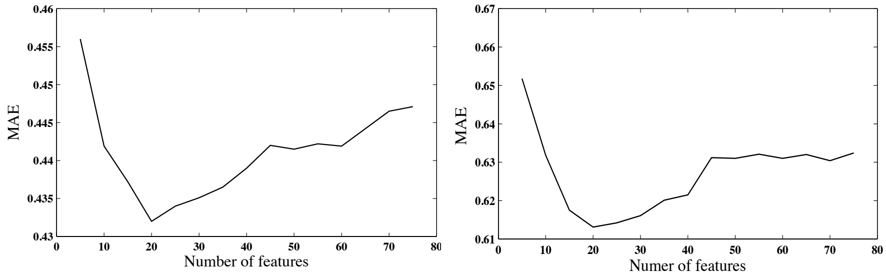


Fig. 5 Error on (a) WMT12 and (b) EAMT11-en-es datasets with all BB features ranked by `GPs`.

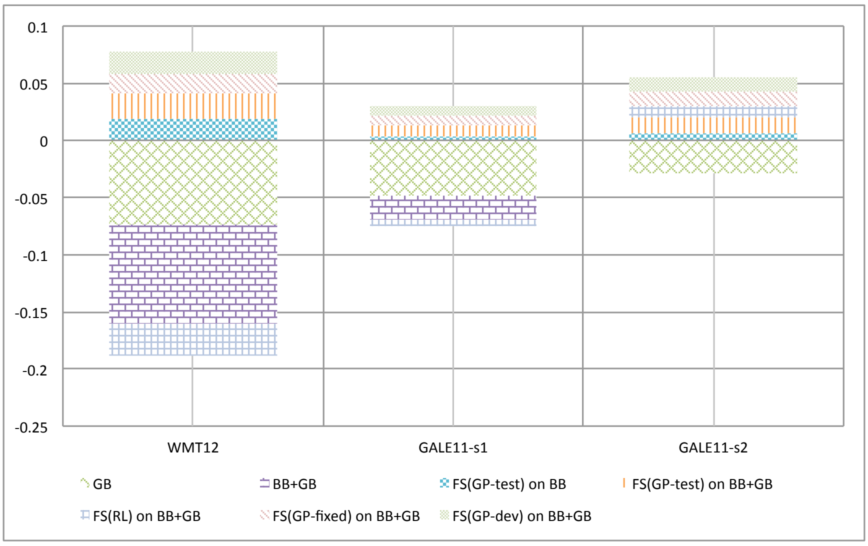


Fig. 6 Improvements of various feature sets over black-box features (AF+PR).

participating in the WMT12 QE shared task. These feature sets are very diverse in terms of the types of features, resources used, and their sizes. As shown in Table 6, we observed similar results: feature selection with `GPs` has the potential to outperform models with all initial feature sets. For these experiments, the significance is checked between system AF trained with `GPs` versus each feature selection techniques. Improvements were observed even on feature sets which had already been produced as a result of some other feature selection technique. Table 6 also shows the official results from the shared task [**?**], which are often different from the results obtained with `GPs` even before feature selection, simply because of differences in the learning algorithms used. In some cases results with `GPs` before feature selection are better, notably for WLV-SHEF – which uses a large set of linguistically-motivated features, showing the potential of `GPs` as a learning algorithm for QE.

Team	System	#features	Official WMT12 score MAE	Official WMT12 score RMSE	Score with GP MAE	Score with GP RMSE
SDL	AF	15*	0.61	0.75	0.6030	0.7510
	FS(GP-dev)	10	-	-	0.6021	0.7479
	FS(GP-fixed)	17	-	-	0.6013	0.7489
	FS(GP-test)	10	-	-	0.6013	0.7474
	FS(RL)	12	-	-	0.6025	0.7513
UU	AF	82	0.64	0.79	0.6507	0.8012
	FS(GP-dev)	13			**0.6425**	**0.7939**
	FS(GP-fixed)	17			**0.6459**	**0.7952**
	FS(GP-test)	10			**0.6419**	**0.7931**
	FS(RL)	67			0.6489	0.7979
Loria	AF	49	0.68	0.82	0.6866	0.8340
	FS(GP-dev)	12	-	-	**0.6824**	0.8355
	FS(GP-fixed)	17	-	-	**0.6829**	0.8351
	FS(GP-test)	10	-	-	**0.6824**	0.8395
	FS(RL)	41	-	-	0.6861	0.8395
UEdin	AF	56	0.68	0.82	0.6949	0.8540
	FS(GP-dev)	16	-	-	**0.6839**	0 **8352**
	FS(GP-fixed)	17	-	-	**0.6825**	0 **8373**
	FS(GP-test)	20	-	-	**0.6795**	**0.8323**
	FS(RL)	49	-	-	0.6899	0.8478
TCD	AF	43	0.68	0.82	0.6906	0.8367
	FS(GP-dev)	12	-	-	0.6906	0.8370
	FS(GP-fixed)	17	-	-	0.6907	0.8372
	FS(GP-test)	10	-	-	0.6904	0.8370
	FS(RL)	37	-	-	0.6913	0.8372
WLV-SHEF	AF	147	0.69	0.85	0.6665	0.8219
	FS(GP-dev)	15	-	-	**0.6611**	**0.8090**
	FS(GP-fixed)	17	-	-	**0.6633**	**0.8105**
	FS(GP-test)	15	-	-	**0.6592**	**0.8088**
	FS(RL)	127	-	-	**0.6658**	**0.8168**
UPC	AF	57	0.84	1.01	0.8365	0.9601
	FS(GP-dev)	13	-	-	**0.8092**	**0.9304**
	FS(GP-fixed)	17	-	-	**0.8115**	**0.9368**
	FS(GP-test)	15	-	-	**0.8092**	**0.9288**
	FS(RL)	46	-	-	0.8302	0.9588
DCU	AF	308	0.75	0.97	0.6782	0.8394
	FS(GP-dev)	15	-	-	**0.6157**	**0.7671**
	FS(GP-fixed)	17	-	-	**0.6211**	**0.7716**
	FS(GP-test)	15	-	-	**0.6137**	**0.7602**
	FS(RL)	215	-	-	**0.6673**	**0.8250**
PRHLT	AF	497	0.70	0.85	0.6733	0.8297
	FS(GP-dev)	24	-	-	**0.6677**	**0.8201**
	FS(GP-fixed)	17	-	-	0.6697	0.8219
	FS(GP-test)	30	-	-	**0.6647**	**0.8179**
	FS(RL)	337	-	-	0.6722	0.8291

Table 6 Results on WMT12 feature sets. * indicates that the initial feature sets already resulted from feature selection.

The error curves on the test sets for different numbers of top-ranked features have a similar shape to those with the common feature sets. As an example, Fig 7 shows the Uppsala University feature set, with the lowest error score for the 15 top-ranked features.

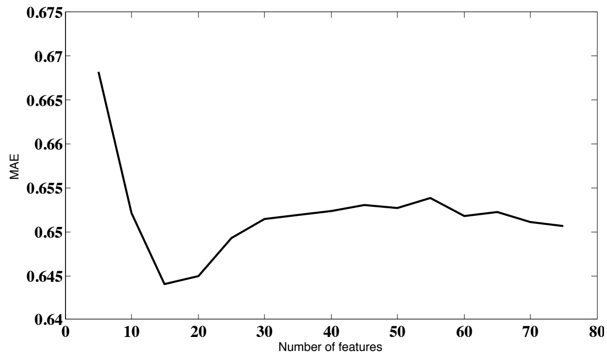


Fig. 7 Error on 82 UU dataset with all features ranked by `GPs`.

5.3 Commonly selected features

Next we investigate whether it is possible to identify a common subset of features which are selected for the optimal feature sets in most datasets. To do that, we took the average rank of each feature across all datasets containing common feature sets. The 10 top and bottom ranked features, along with their average rankings, are shown in Table 7.

Interestingly, not all top ranked features are among the 17 reportedly good baseline features. All of these features are language-independent. Also, most of them are simple and straightforward to extract: they either do not rely on external resources, or use resources that are easily available, such as tools for LM (e.g., SRILM), or word-alignment (e.g., GIZA++).

The same analysis on the feature sets from the WMT12 shared task is not possible, given the very little overlap in features used by the different feature sets.

6 Conclusions and future work

We have presented a number of experiments showing the potential of a promising feature ranking technique based on Gaussian Processes for translation quality estimation. Using an oracle approach to select the number of top-ranked features to train quality estimation models, this technique has been shown to outperform all feature sets available with only a small fraction of their features on a number of datasets with common feature sets. More important, we were able to obtain the same or comparable performance with this technique when selecting the number of features based on a development set, or even based on

Top-ranked feature	**Avg. rank**
source sentence perplexity	9.12
number of mismatched quotation marks	11.28
source sentence perplexity without end of sentence marker	12.57
number of tokens in target	15.59
number of tokens in source	15.61
average number of translations per source word in the sentence (threshold in giza: prob $>$ 0.1)	16.42
LM log probability of POS of the target	18.33
average number of translations per source word in the sentence (threshold in giza: prob $>$ 0.2) weighted by the inverse frequency of each word in the source corpus	19.12
pseudo-reference	19.99
absolute difference between no tokens in source and target normalised by source length	20.45
Bottom-ranked features	Avg. rank
absolute difference between number of commas in source and target	73.10
percentage of distinct unigrams seen in the corpus (in all quartiles)	69.13
average unigram frequency in quartile 3 of frequency (lower frequency words) in the corpus of the source sentence	65.14
absolute difference between number of : in source and target normalised by target length	64.19
absolute difference between number of : in source and target	62.12
percentage of tokens in the target which do not contain only a-z	61.16
number source tokens that do not contain only a-z	61.01
average number of translations per source word in the sentence (threshold in giza: prob $>$ 0.5)	59.66
percentage of punctuation marks in target	59.11
percentage of content words in the target	58.83

Table 7 Top and bottom ranked features based on their average `GP` rank across datasets.

an empirically pre-defined set of features (17). The proposed feature selection technique has also been shown to improve the performance of all participating systems in the WMT12 shared task on quality estimation. Finally, our analysis led to the identification of a set of features which perform well on average across many datasets with different language pairs, machine translation systems, text domains and quality labels.

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