CALIBRATION ANALYSIS FOR NATURAL LANGUAGE PROCESSING SYSTEMS

An Honor Thesis

Presented by

KHANH X. NGUYEN

Approved by:

Brendan O'Connor, School of Computer Science

Erik Learned-Miller, School of Computer Science

ABSTRACT

Title: **Calibration analysis for natural language processing systems**

Author: **Khanh X. Nguyen**

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Approved By: **Brendan O'Connor, School of Computer Science**

Approved By: **Erik Learned-Miller, School of Computer Science**

We argue that measuring the reliability of probabilistic predictions is crucial for mitigating cascaded errors and estimating risks in natural language processing systems. Hence, we propose *calibration analysis* as a new framework for assessing probabilistic predictions. Two methods are presented to report results of the analysis: calibration score and calibration curve. We show that they can be effectively estimated using a simple non-parametric regression method. Moreover, confidence intervals of the estimates can also be constructed. Finally, we apply calibration analysis on different families of probabilistic models to study the effects of model structure and feature on calibration.

CHAPTER 1

INTRODUCTION

Ambiguity in natural languages motivates researchers to use probabilistic models for natural language processing (NLP) tasks. Typically, a probabilistic model produces a posterior distribution over the space of all possible labels of an input. The probability of each label reflects the degree of uncertainty the model carries if it assigns that label to the input. The probabilistic predictions are then translated into final labels based on a decision-making scheme. Most of the time, performance of an NLP model is reported using metrics that only measure how well the predicted labels align with the true labels. The posterior distribution output by the model is, therefore, neglected.

Nevertheless, in the context of NLP pipelines, knowing the quality of posterior predictions are extremely important in mitigating cascaded errors. Methods that uses K-best predictions (Sutton and McCallum, 2005; Wellner et al., 2004; Finkel et al., 2006) instead of using single best predictions weights the labels by their predicted probabilities. Although they were shown to give positive results, we suspect that the full potentials of these methods have not been recognized since they all assume that the tested models produce correct posterior predictions, which is not true in many cases.

Besides that, knowledge about the uncertainty of predictions is useful for users of NLP systems. Reporting uncertainty of a model to its users is essential for risk assessment. Consider two predictions for a binary variable: one assigns a probability of 0.51 that the value of the variable is 1 and the other gives a probability of 0.99 for the same event. Using a threshold of 0.5, they will be both converted to positive

predictions. The users are thus oblivious to the risk they are taking when trusting two predictions equally. On the other hand, if they knew the true uncertainties, we expect that they would trust the former prediction less than the latter one. This type of situation is very common for business users of NLP systems. Prediction confidence score are vital for them in calculating long-term revenue and making investment decisions.

In this thesis, we propose *calibration analysis* as a framework for measuring the quality of the posterior predictions of probabilistic models. Calibration analysis is a powerful assessment tool for three reasons. First, perfect calibration is one of two main characteristics of perfect posterior predictions. Second, calibration analysis is simple to conduct and the results can be easily presented by a numerical score or a visualizable plot. Third, calibration analysis is extremely flexible. It is model-independent and application-independent. It only requires the tested model to output probabilistic predictions of an event of interest. The contributions of this work are three-fold:

1. Review the theoretical foundation of calibration analysis.

2. Present two means of reporting results of the analysis: calibration scoring and calibration curve plotting. Describe adaptive binning as a simple nonparametric regression method for computing them.

3. Apply calibration analysis to investigating calibration patterns of models for POS tagging and coreference resolution. Especially, for coreference resolution, demonstrate a Monte Carlo sampling technique for approximate the probabilistic predictions, which are complicated to derive exactly.

CHAPTER 2

SUMMARY OF WORK OF PREVIOUS RESEARCHERS

Issues on neglecting uncertainty propagation in pipelines that employ single-best decision-making scheme were known for many years (Draper, 1995). Efforts to avoid a pipeline design in NLP were either increasing the model complexity (Singh et al., 2013; Durrett and Klein, 2014) or ineffective (Sutton and McCallum, 2005). Besides that, approaches that preserve the pipeline structure and manage to mitigate cascaded errors such as modifying inference algorithms to obtain K best predictions gave useful improvements (Huang and Chiang, 2005; Toutanova et al., 2005). Finkel et al. (2006) proposed a more clever way to obtain the top predictions using Monte Carlo inference. Unfortunately, in those approaches, the posterior predictions of the models are assumed to be reliable, which does not hold since the models are all imperfect. Performing calibration analysis on the models will be helpful to better understand the effectiveness of those approaches.

The notion of calibration was originally developed in the field of meteorology (Miller, 1962; Murphy, 1973) and was referred to as validity or reliability. Rubin (1984) argued that an applied statistician "should be Bayesian in principle and calibrated to the real world in practice". Murphy and Winkler (1984) proposed a general framework for forecast verification. They proposed two frameworks for analyzing posterior predictions, based on two ways to factorize the joint distribution of prediction and observation. We employ their calibration-refinement framework with a special focus on developing a procedure for measuring miscalibration of NLP models. DeGroot and Fienberg (1983) presented a well-defined theoretical scoring rule for comparing calibration and refinement of forecasters. However, since calculating the

score required knowledge of an unknown realistic distribution of the data, the score could not compute exactly in practice. Threfore, approximation methods from data sample must be used in this case. In fact, estimating realistic distribution is a regression problem where the data points are prediction-observation pairs. Parametric regression models are not flexible enough to generalize calibration patterns of different models. On the other hand, non-parametric models such as local regression (Wasserman, 2006) not only gives better estimates but also provides confidence intervals of the estimates. Adaptive binning is an easily implemented non-parametric method that was proved to be useful in biochemisty and computer vision (Davis et al., 2007; Leow and Li, 2004). Although we favor this method for the purpose of simplicity, more advanced methods are available such as local likelihood (Frölich, 2006).

Assessing uncertainty of probabilistic predictions is standard in many fields such as weather forecasting (Murphy, 1993), economics (Canova, 1994; Cooley, 1997) or earth sciences (Oreskes et al., 1994) but receives little attention in NLP. Calibration studies for general machine learning models Niculescu-Mizil and Caruana (2005); Caruana and Niculescu-Mizil (2006) showed that applying recalibration techniques boosted performances of various models. Although these works also analyzed calibration and refinements of predictions through visualizable plots, they did not provide a concrete metric to quantify the degrees of miscalibration of the models. Our work not only provides more compact calibration plots but also describe an easy-to-implement method to calculate calibration score. Moreover, we also attempt to compute confidence intervals for all of our measurements.

CHAPTER 3

EXPLANATION OF CURRENT METHODOLOGY AND GOALS

3.1 Background

3.1.1 Calibration-refinement framework

Throughout this paper, we will consider a binary prediction problem, where each to-be-predicted instance can either be labeled positive (denoted by 1), or negative (denoted by 0). A probabilistic model for this problem assigns each instance i a *prediction* $q_i \in [0, 1]$, which represents the confidence score that the instance is in the positive class. After the model makes their predictions, the set of true observations will be given for model assessment. The true observation for instance i is denoted by $y_i \in \{0, 1\}$.

Let $S = \{(q_1, y_1), (q_2, y_2), \cdots, (q_N y_N)\}$ be a set of prediction-observation pairs produced by a probabilistic model. Follow Murphy and Winkler (1984), we assume that the elements of S are drawn from a hypothetical joint distribution $P(y, q)$, where y and q are the random variables for the prediction and the true label, respectively. $P(y, q)$ contains all the information needed for analyzing the quality of the predictions. The *calibration-refinement framework* is based on the Bayesian factorization of $P(y, q)$:

$$P(y, q) = P(y \mid q)P(q) \tag{3.1}$$

The conditional probability $P(y = 1 \mid q)$ is called the *realistic frequency* with respect to the prediction value q. It indicates how often the true label turns out to be positive among all instances that are predicted to be positive with a confidence level of q. A model is said to be *perfectly calibrated* (or perfectly reliable) if its

predictions match with their realistic frequencies for all confidence levels. A more formal definition of perfect calibration is presented in section 3.1.2. On the other hand, the marginal distribution $P(q)$ reflects a model's refinement. A model is said to be *refined* (or sharp) if $P(q)$ concentrates about 0 and 1. This characteristic indicates that the model is capable of discriminating instances from the positive class from instances from the negative class.

For a more concrete view of the calibration-refinement framework, consider a classic example: *precipitation forecast*. In this task, the forecaster is required to give an assessment on the likelihood of precipitation of each single day in a period of time. If a reliable forecaster give a prediction such as "There is 30% chance that it will rain tomorrow", we should expect that among all the days on which that type of prediction is announced, exactly 30% of them will be rainy. Moreover, we should also expect the same condition to hold for all types of predictions (between 0 and 1). However, a reliable forecaster is not always a "good" predictor. Consider the scenario when a forecaster always predicts the climatological probability, i.e. the long-term frequency of precipitation, for any day. The forecaster will be perfectly calibrated but his or her predictions would be useless for regions where the climatological likelihood of raining and not raining are equally likely. In those cases, such unrefined predictions imply a lot of uncertainty and do not help with finalizing binary decisions.

As we can see, maintaining calibration allows posterior predictions to be more realistic whereas having refinement in predictions reduces uncertainty in the decision-making process. Hence, calibration and refinement are orthogonal and complementary concepts.

3.1.2 Definition of perfect calibration

Consider the set of prediction-observation pairs S defined in the previous section.

Definition 3.1. Given a value q between 0 and 1, inclusively, the *realistic frequency* with respect to q, denoted by p_q, is defined as:

$$p_q = P(y = 1 \mid q) = \lim_{N \to \infty} \frac{\sum_{i=1}^{n} I\{q_i = q\} I\{y_i = 1\}}{\sum_{i=1}^{N} I\{q_i = q\}}$$

where $I\{.\}$ is the indicator function and $(q_i, y_i) \in S$.

Definition 3.2. A set of prediction-observation pairs S is said to be *perfectly calibrated* if and only if:

$$p_q = q \qquad \forall q \in [0, 1].$$

3.1.3 Measuring miscalibration

When a model does fulfill definition 3.2, we say that it is *miscalibrated*. The notion of miscalibration is more interesting to study than perfect calibration since most NLP models fall into this category. It is a natural tempting to devise a metric that quantifies miscalibration. Following DeGroot and Fienberg (1983), we introduce concepts that are necessary for constructing such a metric.

Definition 3.3. Let p be real number in $[0, 1]$. A *strictly proper scoring rule* specified by an increasing function $g_1(x)$ and a decreasing function $g_2(x)$ is a function of x that has the following form:

$$f(x) = p g_1(x) + (1 - p) g_2(x) \tag{3.2}$$

and satisfies that $f(x)$ is maximized only at $x = p$.

Theorem 3.4. If $g_1(x)$ and $g_2(x)$ specify a strictly proper function rule, the overall score S for predictions for a probabilistic predictive model can be expressed in the form $S = S_1 + S_2$, where

$$\begin{aligned} S_1 &= E_q \left[p_q \left(g_1(q) - g_1(p_q) \right) + (1 - p_q) \left(g_2(q) - g_2(p_q) \right) \right] \\ S_2 &= E_q \left[p_q g_1(p_q) + (1 - p_q) \, g_2(p_q) \right] \end{aligned} \tag{3.3}$$

It can be proved that S_1 and S_2 have the following properties:

1. S_1 is zero only for perfectly calibrated model and negative otherwise.

2. If two model A and B are both perfectly calibrated and A is at least as sharp as B, the value of S_2 will be at least as large for A as it is for B.

Choosing $g_1(x) = (x-1)^2$ and $g_2(x) = x^2$, S_1 becomes the expected mean squared error between probabilistic predictions and the corresponding realistic frequencies:

$$CalibMSE = E_q[p_q - q]^2$$

We will refer to calibration score (CalibScore) as the *square root* of CalibMSE.

3.2 Practical calibration analysis

The realistic frequency p_q defined in section 3.1.2 is an unknown quantity. Therefore, the true value of the calibration score cannot be calculated exactly. A general approach for this problem is to replace p_q in the score's formula by an approximation computed from data. We will describe adaptive binning as a simple method for doing it.

Parametric regression is not an appropriate choice since it would not be flexible enough for exploring different models' calibration patterns. Conversely, non-parametric methods only impose weak assumptions on the model choice but still gives close approximation.

3.2.1 Adaptive binning procedure

Adaptive binning is a modified version of *regressogram* (Wasserman, 2006). Instead of dividing the interval $[0, 1]$ into equally spaced like regressogram does, adaptive binning assigns an equal number of data points to each bin. This is advantageous in

the context of assessing NLP models, where the distribution of predictions is often skewed toward 0 and 1. Adaptive binning ensures that the mid-range approximations have roughly the same standard errors as those near the boundaries.

Concretely, the adaptive binning procedure is described as follows:

Data: A set of n data points $\{(q_1, y_1), (q_2, y_2), \cdots, (q_N, y_N)\}$.

Parameter: bin size b, the number of points in each bin.

Step 1: Sort the data points by q_i in ascending order.

Step 2: Label the k^{th} data point in the sorted order by $\lfloor \frac{k-1}{b} \rfloor + 1$.

Step 3: Put all the points that have the same label in one bin. If the last bin has size less than b, merge it with the second last bin (if exits). Let $\{B_1, B_2, \cdots, B_T\}$ be the set of bins obtained.

Step 4: For all points k in some bin B_i, define:

$$\hat{p}_i = \frac{1}{|B_i|} \sum_{i \in B_i} y_i$$

and

$$\hat{q}_i = \frac{1}{|B_i|} \sum_{i \in B_i} q_i$$

Step 5: The calibration score is calculated as:

$$CalibScore = \sqrt{\frac{1}{N} \sum_{i=1}^{T} |B_i| (\hat{q}_i - \hat{p}_i)^2}$$

3.2.2 Confidence interval estimation

The 95% confidence interval for $\hat{p}_i$ is approximated by:

$$\hat{p}_i \pm 1.96 \hat{se}_i$$

where $\hat{se}_i = \sqrt{\frac{\hat{p}_i(1-\hat{p}_i)}{|B_i|}}$ is the standard error at for the i^{th} bin.

It should be clear that the above formula is only an estimate of the confidence interval and thus does not guarantee true coverage. However, we found that this method is simple to implement and works well in practice.

In order to obtain the confidence interval for the calibration score, we use the following sampling procedure:

Data: A set of approximations $\{\hat{p}_1, \hat{p}_2, \cdots, \hat{p}_T\}$.

Parameter: Number of samples N_s.

Step 1: Sample N_s times. Each time, for i from 1 to T, draw $\hat{p}_i^* \sim \mathcal{N}\left(\hat{p}_i, \hat{se}_i^2\right)$.

Step 2: For each sample, calculate the current calibration score as:

$$\sqrt{\frac{1}{N}\sum_{i=1}^{T}|B_i|(\hat{q}_i - \hat{p}_i^*)^2}$$

Step 3: Report 95% confidence interval for the calibration score as:

$$CalibScore_{avg} \pm 1.96\hat{se}_{score}$$

where $CalibScore_{avg}$ and $\hat{se}_{score}$ are the mean and the standard error of the scores calculated from the samples.

3.3 Visualize calibration

To have a more general view of a model's degree of miscalibration, we can plot on the pairs $(\hat{p}_1, \hat{q}_1), (\hat{p}_2, \hat{q}_2), \cdots, (\hat{p}_T, \hat{q}_T)$ obtained from the adaptive binning procedure and visualize the *calibration curve* of the model. Calibration curve provides a fine-grained insight into the calibration behaviors in various prediction ranges. To be perfectly calibrated, the calibration curve has to coincide with the diagonal line "y = x", or the *perfect calibration curve* (PCC). At places where the curve lies above the PCC, the model predicts with less confidence then it should have done. Conversely, the model is overconfident where the curve is below the PCC.

An advantage of using the points obtained from the adaptive binning procedure in visualizing calibration is that the plot also captures the refinement aspect of the model. The distribution of points' x coordinates corresponds to the distribution of the model's predictions. On the other hand, if using equally spaced bins, one would need an extra plot to demonstrate that distribution.

3.4 Applications of calibration in NLP

Calibration analysis can easily be applied to analyze posterior predictions of models for structure prediction problems. In this setting, binary events are well-defined as polar queries on (sub)structures of the model such as single words, entity-spans or parsing subtrees. It is not necessary to test whether a model is calibrated for all types of queries. Depending on different downstream tasks, we want to have good calibration on different types of queries. Take syntactic parsing as an example. If the downstream tasks is a sentiment analysis tasks, it is important for the model to be reliable in predicting if a phrase is an adjective phrase. For a different application such as coreference resolution, we would care more about noun phrase's boundaries.

3.4.1 Sequence models

Logistic regression has been shown to give better calibrated probabilities than Naive Bayes (Niculescu-Mizil and Caruana, 2005), which makes us hypothesize that discriminative models would be better than generative models in posterior predictions. We take one step towards proving this hypothesis by examining a two popular classes of sequence models for POS tagging, Hidden Markov Models (HMMs) and Conditional Random Fields (CRFs). Elegant dynamic programming algorithms are available for compute the marginal probability of different tag configurations of substrings of a sentence (Finkel et al., 2006). The forward-backward algorithm, often used in training

CRFs, provides an efficient way to compute the marginal probability for substrings of length 1 or 2.

We conduct the first experiment on a regular WSJ data set extracted from CoNLL-2011 (Pradhan et al., 2011). Predicting POS tagging on the WSJ data is a nearly solved problem. Choosing such an easy task, we would like to analyze the behavior of well-calibrated models. Next, we analyze the two models on a more challenging task, predicting POS for tweets (Gimpel et al., 2011). The difficulty of this task does not only come from the linguistic structure of tweets but also from the relatively small size of the data set. The queries we choose to test calibration on are in the form: "Is the current word an X?". In the first experiment, X is the "NN" tag. In the second experiment, we change to predicting the "V" tag since we find that predicting nouns in tweets is still easy for both models.

Importantly, since our focus is on model structure, we only use basic features for CRF in the comparison. Specifically, the feature set consists of only transition features (tag-tag) and emission features (tag-current word). By doing so, we disentangle the advantage of CRF's model assumptions from the advantage of it having more parameters than HMM. Later, we insert more advanced features to investigate effects of features on calibration.

3.4.2 Coreference resolution

Coreference resolution is the task of determining what entities are referred to by which linguistic expressions (mentions). It remains a challenging task in NLP with state-of-the-art techniques are around 60-70% accuracy Durrett and Klein (2013); Yang et al. (2015). In fact, it is still a debate on which coreference system is the state-of-the-art since the methods were tested on various data sets and the results were usually reported in two or three metrics. A negative impact of this fact is that each time a user wants to start up new application domain, he or she has to re-evaluate

a lot of methods. Calibration analysis is suitable for coreference resolution for two reasons. First, when the accuracy scores are all low, a few percentages difference between imperfect models in accuracy are not significant since the models will make unsatisfiable mistakes eventually. At that time, it is more important to choose a model that is capable of truly quantifying its own mistakes so that risks can be estimated and possibly mitigated. Second, calibration analysis is flexible. The calibration query can be altered for different downstream goals as long as the tested model provides a mechanism for calculating confidence scores of the query.

We conduct a calibration analysis on the Berkeley coreference system (Durrett and Klein, 2013) on the CoNLL-2011 data set. The core of this system is a mention-ranking log-linear model that, for each mention, computes the confidence score of that mention referring to itself (singleton) and each of the previous mentions. Entity clusters are implicit during inference and only constructed after the relationships between the mentions have been determined. Unfortunately, due to this structure, the marginal probabilities of crucial queries such as "Does this pair of mentions belong to the same cluster?" is complicated to derive exactly. However, we can still obtain a fairly good estimate of the confidence scores via Monte Carlo sampling. Concretely, we sample directly the distribution ouput by the model and construct the set of clusters for each sample. The approximated confidence score for a query is the empirical proportion of the number of times the answer for the query is yes over a lot of samples.

CHAPTER 4

REPORT AND DISCUSSION OF RESEARCH RESULTS

4.1 Calibration hyper-parameters

Picking the optimal bin size can be done via cross-validation. However, since we have a fairly large amount of data points, we simply set the bin size to be 1000 for POS tagging, 400 for Tweet POS tagging and 10000 for coreference resolution.

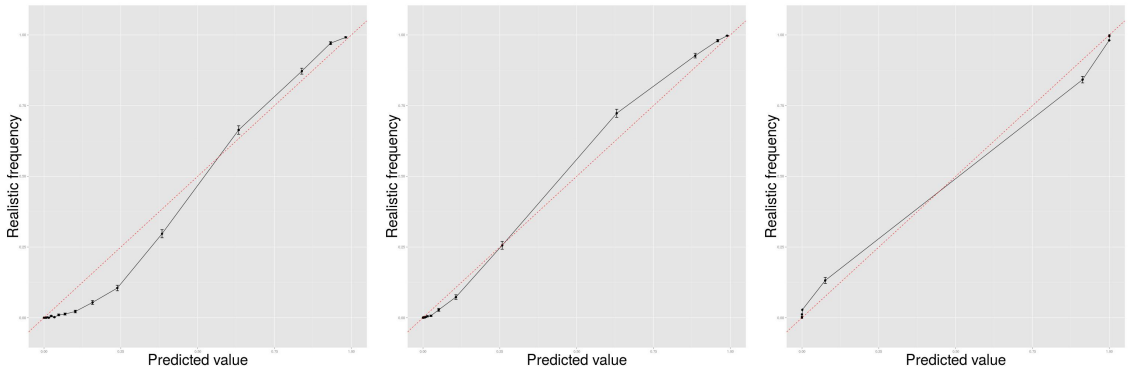
We report the calibration score and its confidence intervals for all our experiments. To compute the score, we implement the method described in section 3.2.2 with a sample of size of 1000.

4.2 Part-of-speech tagging

4.2.1 Data

We extract WSJ articles from the CoNLL-2011 dataset for this experiment. The original data set has already been split the into training, development and testing sets so we filter WSJ articles from each set and join the sentences into together. This process results in 11772 sentences for training, 1632 sentences for development and 1382 sentences for testing. Running the models on the testing set produces 30543 prediction-observation pairs. We then conduct calibration analysis on this set of pairs. The query tested is whether a word has the "NN" tag.

We train a HMM model using maximum likelihood principle. For CRF training, we implement the L2-regularized mini-batch AdaGrad method (Duchi et al., 2011). The batch size is chosen via cross-validation.



(a) (b) (c)

Figure 4.1: Calibration curves for HMM and CRF models (POS tagging) (a) HMM (b) CRF with basic features (c) CRF with advanced features

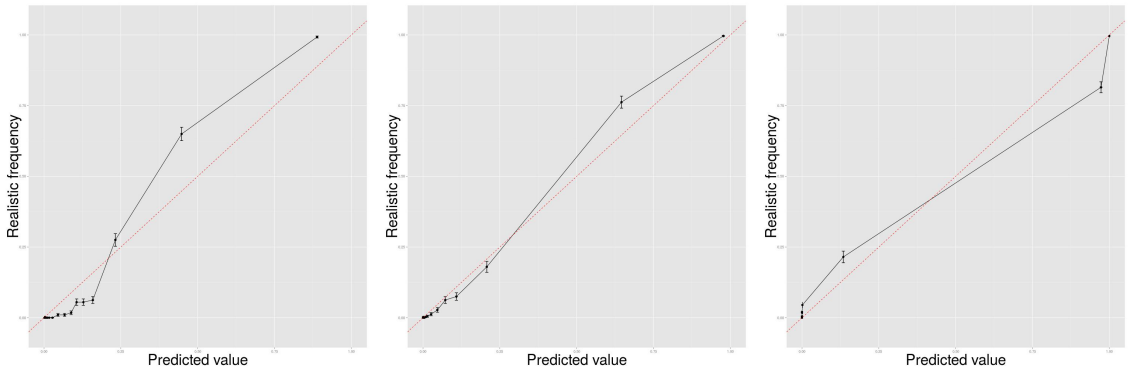
Model	Accuracy (%)	CalibScore
HMM	88.10	0.042 ± 5.27e-5
CRF-Basic	93.02	0.021 ± 6.81e-5
CRF-Advanced	96.08	0.018 ± 6.11e-5

Figure 4.2: Accuracy and calibration scores of the models for POS.

4.2.2 Results

Firstly, we compare HMM with a CRF model with basic features (CRF-Basic). As mentioned in section 3.4.1, CRF-Basic contains only the transition features and the emission features. Figures 4.1(a) and 4.1(b) show calibration curves of the two models. CRF-Basic attains a significantly lower calibration score than HMM does (Figure 4.2). Moreover, the CRF-Basic's calibration has less mid-range points that of HMM, which indicates that the model generates more refined predictions.

To measure the affect of features on calibration, we add advanced features such as surrounding words, word shape, word length, prefixes and suffixes to CRF-Basic. We discover that as we use better features, we obtain more refined and calibrated predictions. The better featurized CRF (CRF-Advanced), which achieves a 96% accuracy on the task, produces a calibration curve just slightly off the PCC (Figure 4.1(c)).



(a) (b) (c)

Figure 4.3: Calibration curves for HMM and CRF models (TweetPOS) (a) HMM (b) CRF with basic features. (c) CRF with advanced features

Model	Accuracy (%)	CalibScore
HMM	67.55	0.075 ± 1.40e-4
CRF (Basic)	78.12	0.034 ± 1.61e-4
CRF (Advanced)	86.19	0.048 ± 1.47e-4

Figure 4.4: Accuracy and calibration scores of the models for TweetPOS.

4.3 Twitter part-of-speech tagging

4.3.1 Data

We repeat the same analysis in section 4.2 predicting POS tags for tweets. For this experiment, we use the ARK's Twitter POS data set (Gimpel et al., 2011), which consists of 1000 sentences for training, 327 sentences for development, 500 sentences for testing. The number of prediction-observation pairs obtain from testing set is 6160. Unlike the regular POS experiment, The query tested is whether a word has the "V" tag since we find that predicting "N" on tweets is still easy for the models.

4.3.2 Results

Comparing between HMM and CRF-Basic, we observe the same pattern as in the section 4.2. CRF-Basic gives a more calibrated and sharper predictions than HMM (Figure 4.3). In both experiments, the calibration score of HMM is always twice as large as that of CRF-Basic. On the other hand, unlike the previous experiment,

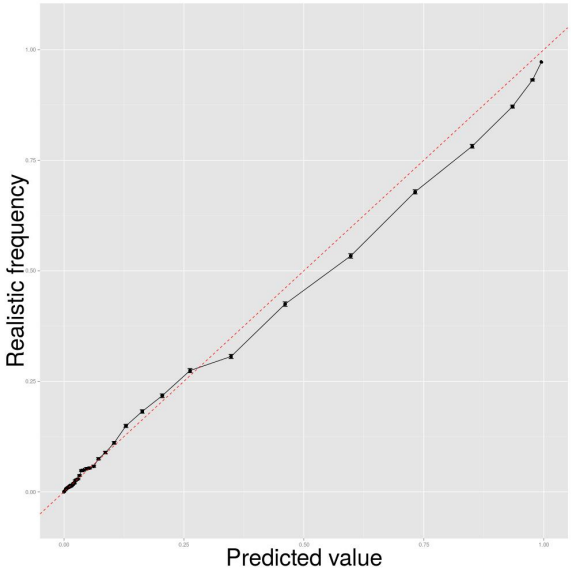


Figure 4.5: Calibration curve of Berkeley-coref.

adding more features to CRF worsens the calibration score (Figure 4.4). While CRF-Advanced produces sharper predictions, it is overconfident at high-score predictions. There are two possible explanations for this phenomenon. First, the data size is smaller; hence, the score may be not approximated well enough. Second, the feature set increases the recall but not the precision of the model.

4.4 Coreference resolution

4.4.1 Data

For this experiment, we use the available implementation of the Bekerley coreference resolution (Berkeley-coref) (Durrett and Klein, 2013). The data set used is the CoNLL-2011 data set. The performance score of this system was around 62% on the development set. The query tested is whether two mentions belong to the same entity. We apply calibration analysis on about 4 millions predictions generated from the development set.

4.4.2 Results

Although having a far-from-perfect accuracy score, the Berkeley's predictions are extremely reliable (Figure 4.5). Its calibration score is 0.007 ± 6.32e-6, much smaller than the models for the easier POS tagging task in the previous sections. The results also help explaining the effect of features on calibration. Berkeley-coref employs a carefully selected set of features called SURFACE. Whereas in the TweetPOS experiment, we see that adding features can degrade calibration, in this experiment, we observe a model with a good set of features can be very reliable despite making a lot of mistakes. The result of this experiment also confirms that discriminative models, with quality features, produces highly reliable predictions.

CHAPTER 5

CONCLUSIONS AND IMPLICATION FOR FUTURE RESEARCH

In this thesis, we have presented calibration analysis as a new framework for evaluating NLP probabilistic models. This framework directly measures the quality of posterior predictions rather than the quality of the final predictions. It is useful for investigating cascaded errors and estimating risks in NLP pipelines, whether the downstream tasks are stated explicitly or not. We propose two mechanisms to communicate the analysis results with the users, calibration score and calibration curve, and describe procedures to construct them. Since calibration analysis is not a common practice in NLP research, we choose to introduce fairly simple procedure so that researchers can implement for themselves. However, for this reason, approximations of the realistic frequencies involve errors. Hence, the confidence intervals constructed are also imperfect. In the future, we would like to reduce those errors by using more advanced non-parametric regression methods such as local likelihood, whose theoretical bounds have been well-studied. On the other hand, we would like apply our calibration analysis to obtain more insights into the behaviors of probabilistic models. In our experiments, discriminative models tend give better calibrated predictions than generative models. But does this fact also affect by the nature of data? Besides that, we would like to know if calibration of a type of query can infer calibration of other related types. Last but not least, a important question to ask was how calibration of an individual model would improve the overall performance of the entire pipeline. Answering this question requires setting up an end-to-end NLP pipeline and a study on recalibration methods.

CHAPTER 6

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I want to dedicate this thesis to my loved ones.

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My sweetest words will be for my love, Huyen. When I am awake, she is asleep. When she sees the sun, I am already in my bed. But we still find time to encourage each other, and to practice generosity, tolerance and optimism together. We share the dream of being better people. Completing this thesis is my first attempt to fulfill that dream with her.

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