We introduce the problem of Automatic Location Type Classification from social media posts. Our goal is to correctly associate a set of messages posted in a small radius around a given location with their corresponding location type, e.g., school, church, restaurant or museum. We provide a dataset of locations associated with tweets posted in close geographical proximity. We explore two approaches to the problem: (a) a pipeline approach where each message is first classified, and then the location associated with the message set is inferred from the individual message labels; and (b) a joint approach where the individual messages are simultaneously processed to yield the desired location type. Our results demonstrate the superiority of the joint approach. Moreover, we show that due to the unique structure of the problem, where weakly-related messages are jointly processed to yield a single final label, simpler linear classifiers outperform deep neural network alternatives that have shown superior performance in previous text classification tasks.\(^1\)

**ACM Reference Format:**
Kravi, Elad, Kimelfeld, Benny, Kanza, Yaron, and Reichart, Roi. 2020. Automatic Location Type Classification From Social-Media Posts. In Proceedings of ACM Conference (Conference’17). ACM, New York, NY, USA, 7 pages. https://doi.org/10.1145/nnnnnn.nnnnnnn

1 INTRODUCTION

Over the last decade, social media has become a prominent channel for information exchange and opinion communication. Thanks to emerging microblog platforms like Twitter and Instagram, a large number of information- and opinion-bearing social media posts have become available and attracted the attention of the research community. This has resulted in growing popularity of tasks such as sentiment analysis [5, 34, 36], recommendation mining [24, 41] and information extraction [4] from such social media posts.

\(^1\)Our code and data will be made available at [URL].
the properties of messages posted in different locations and design hand-crafted features that aim to capture location-level properties (§ 4).

We consider two approaches to our problem (§ 5). In the first, pipeline approach a classifier first classifies each individual tweet in the set and then an aggregation method infers the final location type of the entire set. In the second, joint approach, a single classifier simultaneously processes all the messages in the set to infer the type of their location. For both approaches we implement methods based on traditional linear classifiers and methods based on state-of-the-art convolutional neural networks (CNNs) that have shown superior text classification performance in a number of studies (e.g. [16]).

We further consider four different sets of hand-crafted features – from surface textural features, through simple linguistic features to spatio-temporal features – as well as features based on word embeddings.

Our results (§ 6) demonstrate the power of the joint approach. Moreover, while CNNs and linear classifiers perform similarly in the classification of individual messages, we show that for Automatic Location Type Classification, which requires the processing of a set of weakly-related messages, linear classifiers perform better. Moreover, we show that the simplest surface and linguistic features are most useful for the task.

2 RELATED WORK

In this paper we consider a specific type of the text classification task. The two properties we consider most crucial for our task are: (a) the classification of a set of weakly related messages into a single class; and (b) the association of the message set with a location type. This section reflects our view: We first consider text classification and the different approaches proposed to text representation within this line of work and then discuss previous work on place classification.

Text classification: Features and models. Text classification has been extensively studied in the NLP literature for many years. The standard approach to this task has long been to manually extract features from the text and use this representation for classifier training [27]. Previous works on the task defer in the features they used and the classifiers they employed.

The most famous representation in text classification is bag-of-words. In recent years this approach was extended in various ways. For example, it was augmented with sparsity-inducing regularizers [40] as well as information about (latent) linguistics structures such as parse trees, topics, and hierarchical word clusters [39]. Surveying the various methods based on this representation is beyond the scope of this paper. In our models when using hand-crafted features we consider the vanilla bag-of-words features, as well as features based on POS tags and on language modeling.

Recently, NNs have shown very useful in solving text classification tasks. Some methods first learn word embeddings [29, 31] and derive a text representation that is then employed in a classifier [3]. Others directly learn a vector representation of the entire text [9, 17, 37] and feed them to a classifier. Such methods sometimes include direct application of recurrent neural networks (RNNs and LSTMs [14]) [17, 44] and auto-encoders [11, 43]. Finally, some methods employ NNs to solve text classification tasks in an end-to-end manner. For example, [16] employed a CNN for text classification with very strong results.

A particular challenge our task poses for structure-aware NNs such as CNNs and LSTMs is that the messages we consider for each location are only weakly-dependent, as they are authored by different people and at different times. Our experiments with CNNs – which demonstrated state-of-the-art results in many types of text classification tasks, when compared both to classifiers with hand-crafted features and to other types of NNs [42] – demonstrate that the task is still challenging for structure-aware NNs.

Place and landmark classification. The task that is most similar to ours is that of Twitter user geo-location. Given a set of messages posted by a user, the goal of this task is to identify its location (e.g. (latitude,longitude) coordinates, the center of the closest city etc.) based on the content of its messages (e.g. [1, 23, 33, 35]). This body of work differs from ours as it aims to exploit the geographical biases of language use, both of individuals and in inter-personal communication. In both cases, the assumption is that users who live in the same geographic area share similar features, and the goal is to identify broad geographical areas associated with a user (e.g. a city or a state). Our goal, in contrast, is to identify semantic properties of fine-grained locations (e.g. whether they function as a restaurant or as a health institute).

In the computer vision community there has been some interest in image set classification into a shared label. For example [2, 13, 25, 26] aimed to classify a set of object images to a single label, while in landmark classification [18, 22], given a set of images sent from nearby location the goal is to detect the landmark the set represents.

3 AUTOMATIC LOCATION TYPE CLASSIFICATION

Task Definition. A spatio-textual message is denoted by \( m = (l, c) \) where \( l \) is the location of the message, given in longitude and latitude and \( c \) is its textual content. The input for the Automatic Location Type Classification problem is an entity \( e \) and a set \( M = \{ m_i \}_{i=1}^n \) of all the geo-tagged messages whose distance from \( e \) does not exceed a given radius \( r \). The goal of the task is to correctly classify \( e \) to a label taken from a finite known label set, \( L \), referring to location types such as a restaurant, school, church etc. We would like to apply a machine learning approach for this problem, and set the goal to learn a function \( F: (e, M) \rightarrow \{1, 2 \} \). We will employ a standard supervised approach for minimizing the loss for a labeled training set.

3.1 Learning Approaches

As mention in § 1 the main challenges in our problem are: (1) coping with noisy messages within \( M \), where the noise is defined with respect to the task. That is, noisy messages are those that are sent from the proximity of a location, but their content is not related to the location type; and (2) learning associations among messages in \( M \) that could assist classification, e.g., we can conclude that a place is a church if many messages were posted on Sunday.

We now describe how we tackle these challenges by the following two approaches: (a) Two-Step (pipeline) Classification: classifying each message in the set \( M \) and then classifying \( M \) based on the classifications of its elements; and (b) One-Step (joint) Classification: simultaneously processing all the messages in the set \( M \) and deciding on the location type of \( M \).
Two-Step (Pipeline) Classification. In this approach we partition the problem into two easier problems: first, classify each single message by training a message-level classifier, and then classify the set $M$ based on the labels of the messages it consists of. The approach we apply here for the second step is to compare the predicted label distribution according to the classifier of the first step, to the label distribution of each location type in the training set (see § 5).

The pros and cons of this approach stem from its simplicity. Particularly, it decomposes the processing of the content of individual messages (first step) from the global decision that takes into account the label distribution of different location types (second step). While this facilitates two simple classification steps, it also results in partially-informed decisions at both steps.

One-Step (Joint) Classification. In this approach we learn a single model that jointly considers both the content of individual messages and their association. The pros and cons of this approach are complementary to those of the pipeline approach. Particularly, when jointly considering the entire set of messages, it is hard to set any particular order between the messages: messages posted in the same location are authored by different users and their temporal order does not necessarily reflect the connection between them. While the Joint Model is more complex than the Pipeline Model, it does consider the content of the various messages in $M$ when making the location-type decision and does not decompose the problem into a series of local problems as the pipeline model does.

![Figure 1: One vs. Two Step Classification.](image)

4 DATASET

Our dataset consists of messages posted on Twitter. The dataset consists of 14.5 million geo-tagged tweets from the Manhattan area, collected using the developers API during a period of 400 days, between the years 2012 and 2014. Each record consists of the textual content of the message as well the coordinates from which it was sent and a time-stamp.

We consider six location types: schools, universities, churches, health locations, large shops and museums. The location types were defined based on the NYC Open Data website and the Data Gov website that include the coordinates for the center-of-mass of each location. We collected all the tweets within a distance of 20 meters around each location. This distance was chosen to overcome inaccuracies in GPS location measurements that are known to be about several meters, while maximizing the association between messages and the location they were sent from. Locations associated with less than 5 tweets were not included.

We observed a large variance in the number of messages posted from locations of the same type. For example, shops located near Times Square are typically associated with many more tweets than shops located in the upper west side. Hence, we applied the following process: let $|M_v|$ denote the number of messages posted in a location $v$ and let $\overline{|M_v|}$ denote the average number of tweets for $v$’s location type. If $|M_v|$ was smaller than $\overline{|M_v|}$ we included all the messages $M_v$ in the dataset; otherwise, we picked $\overline{|M_v|}$ random messages from $M_v$. The resulting dataset consists of 988 locations and about 138000 tweets (see Table 1).

To facilitate further research on our problem, our dataset will be made publicly available for the research community. We next provide some details about our dataset.

4.1 Dataset Properties

Here we analyze the properties of our dataset, characterizing the differences between location types. This will help us design classifier features.

Language modeling. In order to characterize the unique lexical properties of each class (location type) we perform a language model (LM) analysis. Particularly, we train bi-gram LMs for each location type and compare them to the same LM when trained on all the tweets in our dataset. We then consider the $k$ terms that contribute the most to the KL-distance [20] between the two types of LMs. The results are presented in Table 2.

It can be seen that some bi-grams represent the venue type (“High School”, “York Academy”, “New Museum”, “Cathedral of”, “Community Health”) while others represent a specific venue (“Cornell Medical”, “Apple Store”). However, many other co-occurrences are seemingly irrelevant to our task (“Below New”, “86th Street”, “Central Terminal”, “City of”, “Junior League”), and were probably generated by noisy tweets (recall their definition in § 1). Lexical information hence seems to be relevant but not sufficient for our task.

Distance from entity location. We next consider the distance of each message from its location. Our assumption is that distances may be indicators of relevance and hence the closer the messages of a given location are to the its coordinates, the stronger the signal that we can expect from the content of these messages. We aggregated the tweets to three classes: adjacent: up to 5 meters, near: 5 – 12 meters and far: 12 – 20 meters.

We found the majority of tweets in museums were sent from adjacent locations (49%), while the majority of tweets from schools, universities and health venues were sent from far locations (65.4%, 66.2% and 65.6%, respectively). The distances of tweets sent from shops and churches are roughly evenly distributed between the classes.

We hypothesize that the reason for this pattern is that museums tend to be isolated, while educational and health institutes may restrict usage of cellphones within nearby surroundings. This may also indicate the coherence of tweets sent from museums in comparison

---

5.wwww.twitter.com
6.https://opendata.cityofnewyork.us
4.https://www.data.gov/
Table 1: Dataset properties. The table presents the distribution of locations (top table section) and tweets (bottom section) and the type-to-token ratio for the tweets of each location.

| LOCATIONS | SCHOOLS | UNIVERSITIES | CHURCHES | SHOPS | MUSEUMS | HEALTH | TOTAL |
|-----------|---------|--------------|----------|-------|---------|--------|-------|
| #         | 323     | 79           | 152      | 97    | 64      | 273    | 988   |
| %         | 32.69%  | 8%           | 15.38%   | 9.82% | 6.48%   | 27.63% | -     |
| TWEETS    | 9626    | 7811         | 37088    | 44038 | 27560   | 11612  | 137735|
| %         | 6.99%   | 5.67%        | 26.93%   | 31.97%| 20.01%  | 8.43%  | -     |
| # TWEETS | 174.01  | 414.44       | 1141.89  | 1275.91| 91.56   | 139.41 |
| %         | 91.56%  | 64.3%        | 17.3%    | 16.1% | 7.2%    | 10.3%  | -     |

Table 2: Most distinguishing bi-grams for each class. The analysis is based on the KL-distance between the class-specific LM and the background LM.

| SCHOOLS       | UNIVERSITIES | CHURCHES       | SHOPS         | MUSEUMS      | HEALTH       |
|---------------|--------------|----------------|---------------|--------------|--------------|
| Manhattan     | Cornell Medical | Church of of St. | Apple Store @ Manhattan | Museum of Cinemas 86th | |
| /Upper East of St. | York Institute | New York-Presbyterian | @ Manhattan | Intrepid Sea, | |
| High School   | New York- Presbyterian | Church of of St. | Grand Central | Sea, Air | Community Health |
| Road Runners  | York Academy  | John the       | Manhattan, NY at Apple | Air &amp; @ Intrepid | |
| Riverside Church | Assembly West | Memorial Preview | Central Terminal @ Intrepid | Space Museum | |
| York Road     | New Work      | Preview Site   | Forbidden Planet | New Museum | |
| Divine, NYC   | Work City     | @ Cathedral    | Central Terminal | @ Intrepid | |
| Runners - the Divine | Medical Center | the Divine | Dover Street | City of | |
| Luke in       | Academy of    | Cathedral of Roman Catholic | Street Market | @ Museum | |
|               | Below (New)  | Manhattan, New | Manhattan, New | Harlem World | |

Part-Of-Speech distribution. We applied the Stanford’s POS tagger [38] to messages sent from each location type. Figure 2 compares the prevalence of four major POS tags (NN, NNP, VB and PRP) in the different location types. We also measured other POS tags like adjectives, but no significant difference was found between the classes.

It can be seen that messages sent from schools have a larger proportion of (non-proper) nouns, verbs and pronouns and a smaller proportion of proper nouns, indicating a more simple language (e.g. “I need to get my life together right about now lol”, “Dear iphone, I am never trying to say ducked up”) which may be indicative of the young age of the senders. This finding is in line with previous studies about language learning [7]. Universities and churches have similar POS distributions. Museums, have a large proportion of proper nouns and a smaller proportion of personal pronouns in comparison to the overall statistics (27.4% vs 21.4% and 3.1% vs 4.3%). This can be explained by the many names associated with art (e.g., famous painters and artists). Health locations have a smaller proportion of proper nouns, and a larger proportion of verbs. Messages sent from shops have a similar distribution to that of the background messages, indicating a general, non-unique language.

Temporal analysis. We further categorized the tweets to six categories, reflecting their sending time: Morning: 7 to 11 AM, Noon: 11 AM to 3 PM, Afternoon: 3 to 6 PM, Evening: 6 to 9 PM, Night: 9 PM to midnight, Late night: midnight to 4 AM and Dawn: 4 to 7 AM. Figure 3 presents the class distribution of the messages of each location type as well as of the entire set of messages.

As expected, schools and universities are more active during morning and noon time, museums are more active during noons and afternoons and shops are more active during afternoon and evening times. Yet, while the temporal signal is valuable, it cannot differentiate the classes without further information from other sources.

5 MODELS

We design our models so that we can answer three related questions: (1) which approach performs better: pipeline or joint (§ 3)? (2) which class of models is more suitable: linear classifiers or deep
We first describe our feature-set which is based on the analysis of words and the number of characters in the message (binned into (d) Time of the day: the time of day in which the message was sent, according to the six classes described in § 4.1. We experiment with each combination of the four feature sets, and report results with the combination that performs best on the development set.

5.1 Linear Classification

We first describe our feature-set which is based on the analysis of § 4. We then discuss the implementation of the pipeline and the joint approaches.

Features. We consider four feature sets. The set of basic textual features consists of surface-level features such as the number of words and the number of characters in the message (binned into n-gram features consists of counts of word n-grams, where we considered $n=1, 2$, with a threshold of 5 appearances in the training set.

The set of NLP features consists of: (a) LM scores: for each location class, $T$, we trained an LM, $M_T$, on its messages. Then we score each message, $m$, in the training set according to each class-specific LM. Scores are calculated using the query likelihood (QL) metric [32]: $QL(m, M_T) = \Pr(M_T|M_T) = \prod_t p(t|M_T)$, where $t$ are the tokens of $m$ and the term probabilities are computed with Dirichlet smoothing [28]; and (b) POS tags: we encode the counts of 13 major POS tags for each message: ’CD’, ’DT’, ’FW’, ’IN’, ’JJ’, ’NN’, ’NNP’, ’NNPS’, ’PRP’, ’RB’, ’VB’, ’VBP’, ’VBG’.

Finally, the set of spatio-temporal features consists of: (c) Distance from the classified entity: we encode the Haversine distance [19]7 of the message from the classified entity, measured in meters; and (d) Time of the day: the time of day in which the message was sent, according to the six classes described in § 4.1. We experiment with each combination of the four feature sets, and report results with the combination that performs best on the development set.

Pipeline classification. For the first step we train a classifier for individual messages using the above features. We considered Logit [12] and Naive Bayes [30] classifiers. When applying these classifiers to test messages, we consider for each message the label with the maximal probability according to the model. 8 For the second step, we compare the label (location type) proportion among the individual messages as decided by the first step classifier (the induced proportion), to the gold-standard label proportion of the training set messages (the background proportion), and pick the label with the highest positive difference between the induced and the background proportions.

Joint classification. For this approach we first concatenate all the messages from the location and then compute the n-gram features as well as LM-based and POS-based features (feature type (a) and (b) above). We did not use Distance and Time features (types (c) and (d)) as they are computed for individual messages. We then train the same classifiers of the pipeline approach.

Clearly, the linear classifiers reflect a structure-ignorant approach. That is, since it is hard to characterize the structure of the message set, this approach just ignores it and treats the messages as independent of each other.

5.2 Deep Neural Networks

We compare two types of DNNs: convolution neural networks CNN [21] and recurrent neural networks including LSTM and bi-directional LSTM [6]. While we explored a variety of recurrent network architectures, they were all substantially outperformed by the CNNs. We hence do not report results for this class of methods.

The input for the CNN is a tensor of word embeddings: we used Glove embeddings [31], trained on the Twitter dataset with dimension of 200.9 Following [16] we employ $K$ filters in sizes of $d=3, 4, 5$ times the embedding domain, $d$, each iterating the input matrix in a sliding window generating a $1 \times (n - d + 1)$ size vector, where $n$ is the input text length. A max pooling is then performed for each of the $K$ vectors to generate a single $1 \times K$ vector that is fed to the classification (softmax) layer.10

Pipeline classification. We store the embeddings of the words of each message in a matrix of size $|W| \times d$ where $|W|$ is the number of words and $d$ is the embedding dimension. After classifying each message we apply the same distribution-based approach described for pipeline classification in § 5.1.

Joint classification. Following [9] we averaged the embeddings of the words in each message. For comparison, we also implemented this approach where each tweet is represented by the sentence embedding method of [8],11 with the same word embeddings fed to the sentence embedding algorithm. The columns of the resulting matrix contain the embeddings of all the messages sent from a single location.

Like with the linear classifiers, the pipeline approach again reflects a structure-ignorant approach. The joint classification approach, on the other hand, assumes a connection between the messages. As pointed by [15] the input order for a CNN impacts its performance, and in our case we expect a particular importance for this order as it reflects the relations between the messages sent from the classified location.

We considered three message sorting methods: (1) by distance from the location, starting from nearest to the most distant message; (2) by LM score: We considered the scores given by the LMs of all location types and assigned a message to the LM that gives it

7https://en.wikipedia.org/wiki/Haversine_formula
8Code for the classifiers is taken from https://nlp.stanford.edu/wiki/Software/Classifier.
9http://nlp.stanford.edu/data/glove.twitter.27B.zip
10Our DNN models were implemented with Deeplearning4j: http://deeplearning4j.org.
11https://github.com/facebookresearch/InferSent
We report results with two measures: accuracy and class-based F1 score. We run a 10-fold cross-validation protocol with random sampling across locations for joint models and across messages for pipeline models, and report the averaged result of each model across the 10 folds. The train/dev/test ratio in each fold is 64:16:20. We provide hyper-parameter information in the supp. material.

Table 3 presents our results, that shed light on the questions we raised throughout the paper. First, joint (one-step) classification substantially outperforms the majority class and random selection baselines, the best pipeline approach does that only for F1 but not for accuracy. This indicates the power of joint modeling of the entire set of messages in our task.

Next, for both the pipeline and the joint approaches it is a linear classifier that performs best. Interestingly, for individual messages CNN and the linear classifiers perform similarly (bottom table), the performance gap is in the main task of location type classification. Since the linear classifiers do not consider the relations between the messages, we consider this result as another indication of the challenge the unique structure of our task (modeling weakly-related messages) poses for structure-aware modeling. In fact, as noted in § 5, the results we report for CNN are with random message ordering, as our more informed ordering strategies failed to improve results.

Interestingly, for the best performing models in both joint and pipeline learning, LM and POS-based features are not included in the best feature configuration according to the development data experiments. Hence, we do not report test-set results for these features here. For the best performing model (logit, joint approach) the spatio-textual features are also not included in the best feature configuration, as they are not considered in the joint approach (§ 5). This pattern emphasizes the importance of shallow textual features for our task and the need for further research into more sophisticated linguistic features as well as the collection of more relevant contextual information regarding the time, location and geography of the messages.

Finally, our choice of hand-crafted features is also supported by an experiment where we trained the linear models with word embedding features (results are not shown in the table). In the pipeline approach we represented each message by the average of its word embeddings, while in the joint approach an entire set of messages is represented by the average of its word embeddings. The resulting models were substantially outperformed by the best linear models trained with hand-crafted features. For example, in the joint approach the logit classifier scores 31.5 in accuracy and 9.1 in F1 (not shown in the table), compared to the respective 52.6 and 48.8 scores of the best pipeline model (logit with n-grams and textual features) achieving accuracy and F1-score of 52.6 and 48.8, respectively, while the best pipeline (two-steps) model scores only 27.7 and 34.7 in these measures, respectively. While the best joint model substantially outperformed the majority class and random selection baselines, the best pipeline approach does that only for F1 but not for accuracy. This indicates the power of joint modeling of the entire set of messages in our task.

7 CONCLUSION

We studied the task of Automatic Location Type Classification from a set of messages posted in microblogs (tweets). We constructed a new dataset for the task, which will be made available on-line to facilitate further research. Moreover, we analyzed a large number of modeling choices: pipeline vs. joint modeling, hand-crafted vs. automatically-learned features and linear (structure-ignorant) vs. DNN-based (structure-aware) classification. Our experiments support the joint approach that jointly processes the entire set of messages from the same location.

The most powerful features we considered were the most shallow ones: textual and n-gram features, while NLP and spatio-textual features were not included in the best feature configurations. Moreover,
linear models that do not explicitly account for inter-message connections outperformed the CNN. For DNNs we also observed that exploiting distance and language modeling information for message ordering failed to improve over random ordering. In future work we hence intend to further explore contextual features as well as more elaborated linguistic features, and to design structure-aware models that properly account for the inter-message relations in our dataset.

REFERENCES
[1] Amr Ahmed, Liangjie Hong, and Alexander J Smola. 2013. Hierarchical geographical modeling of user locations from social media posts. In Proceedings of the 22nd international conference on World Wide Web.
[2] Oguzen Arandjelovic, Gregory Shakhnarovich, John Fisher, Roberto Cipolla, and Trevor Darrell. 2005. Face recognition with image sets using manifold density divergence. In Computer Vision and Pattern Recognition, 2005. CVPR 2005. IEEE Computer Society Conference on, volume 1, pages 581–588. IEEE.
[3] Sanjeev Arora, Yingyu Liang, and Tengyu Ma. 2017. A simple but tough-to-beat baseline for sentence embeddings. In Proc. of ICLR.
[4] Edward Benson, Aria Haghighi, and Regina Barzilay. 2011. Event discovery in social media feeds. In Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies-Volume 1.
[5] Johan Bollen, Huina Mao, and Xiaojun Zeng. 2011. Twitter mood predicts the stock market. Journal of computational science, 2(1):1–8.
[6] Jason PC Chiu and Eric Nicholas. 2016. Named entity recognition with bidirectional lstm-cnns. Transactions of the Association of Computational Linguistics, 4(1):357–370.
[7] Kevyn Collins-Thompson and James P Callan. 2004. A language modeling approach to predicting reading difficulty. In Proceedings of the Human Language Technology Conference of the North American Chapter of the Association for Computational Linguistics:HLT-NAACL, 2004.
[8] Alexis Conneau, Douwe Kiela, Holger Schwenk, Loïc Barrault, and Antoine Bordes. 2017. Supervised learning of universal sentence representations from natural language inference data. In Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing, pages 670–680, Copenhagen, Denmark. Association for Computational Linguistics.
[9] Andrew M Dai, Christopher Olah, and Quoc V Le. 2015. Document embedding with paragraph vectors. arXiv preprint arXiv:1507.07998.
[10] Jacob Eisenstein. 2013. What to do about bad language on the internet. In Proceedings of the 2013 conference of the North American Chapter of the association for computational linguistics: Human language technologies, pages 359–369.
[11] Xavier Glorot, Antoine Bordes, and Yoshua Bengio. 2011. Domain adaptation for large-scale sentiment classification: A deep learning approach. In Proc. of ICML.
[12] Jerry Hausman and Daniel McFadden. 1984. Specification tests for the multinomial logit model. Econometrica: Journal of the Econometric Society, pages 1219–1240.
[13] Munawar Hayat, Mohammed Bennamoun, and Senjansc An. 2015. Deep reconstruction models for image set classification. IEEE transactions on pattern analysis and machine intelligence, 37(4):713–727.
[14] Sepp Hochreiter and Jürgen Schmidhuber. 1997. Long short-term memory. Neural computation, 9(8):1735–1780.
[15] Elad Hoffer, Shai Fine, and Daniel Soudry. 2018. On the blindspots of convolutional neural networks. CoRR, abs/1802.05187.
[16] Yoon Kim. 2014. Convolutional neural networks for sentence classification. In In proc. of EMNLP.
[17] Ryan Kiros, Yukun Zhu, Ruslan R Salakhutdinov, Richard Zemel, Raquel Urtasun, Antonio Torralba, and Sanja Fidler. 2015. Skip-thought vectors. In Advances in neural information processing systems, pages 3294–3302.
[18] Jan Knopp, Josef Sivic, and Daniel Pajdla. 2010. Avoiding confusing features in place recognition. In European Conference on Computer Vision, pages 748–761. Springer.
[19] Granino Arthur Korn and Theresa M Korn. 2000. Mathematical handbook for scientists and engineers: definitions, theorems, and formulas for reference and review. Courier Corporation.
[20] Solomon Kullback and Richard A Leibler. 1951. On information and sufficiency. The annals of mathematical statistics, 22(1):79–86.
[21] Yann LeCun, Léon Bottou, Yoshua Bengio, and Patrick Haffner. 1998. Gradient-based learning applied to document recognition. Proceedings of the IEEE, 86(11):2278–2324.
[22] Yunpeng Li, David J Crandall, and Daniel P Huttenlocher. 2009. Landmark classification in large-scale image collections. In Computer vision, 2009 IEEE 12th international conference on, pages 1957–1964. IEEE.
[23] Michael D Lieberman, Hanan Samet, and Jagan Sankaranarayanan. 2010. Geocoding with local lexicons to build indexes for textually-specified spatial data. In Data Engineering (ICDE), 2010 IEEE 26th International Conference on. IEEE.
[24] Jovian Lin, Kazunari Sugiyama, Min-Yen Kan, and Tat-Seng Chua. 2013. Addressing cold-start in app recommendation: latent user models constructed from twitter followers. In Proceedings of the 36th international ACM SIGIR conference on Research and development in information retrieval, pages 283–292. ACM.
[25] Jiwen Lu, Gang Wang, and Jie Zhou. 2017. Simultaneous feature and dictionary learning for image set based face recognition. IEEE Transactions on Image Processing, 26(8):4042-4054.
[26] Angshul Majumdar,Richa Singh, and Mayank Vatsa. 2017. Face verification via class sparsity based supervised encoding. IEEE transactions on pattern analysis and machine intelligence, 39(6):1273–1280.
[27] Christopher Manning and Dan Klein. 2003. Optimization, maze models, and conditional estimation without magic. In Proceedings of the 2003 Conference of the North American Chapter of the Association for Computational Linguistics on Human Language Technology: Tutorials-Volume 5, pages 8–8. Association for Computational Linguistics.
[28] Christopher D Manning, Prabhakar Raghavan, Hinrich Schütze, et al. 2008. Introduction to information retrieval. 1. Cambridge university press Cambridge.
[29] Tomas Mikolov, Ilya Sutskever, Kai Chen, Greg S Corrado, and Jeff Dean. 2013. Distributed representations of words and phrases and their compositionality. In Proc. of NIPS.
[30] Kevin P Murphy. 2006. Naïve bayes classifiers. University of British Columbia, 18.
[31] Jeffrey Pennington, Richard Socher, and Christopher Manning. 2014. Glove: Global vectors for word representation. In Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP), pages 1532–1543.
[32] Jay M Ponte and W Bruce Croft. 1998. A language modeling approach to information retrieval. In Proceedings of the 21st annual international ACM SIGIR conference on Research and development in information retrieval, pages 275–281. ACM.
[33] Afshin Rahimi, Trevor Cohn, and Timothy Baldwin. 2017. A neural model for user geolocating and lexical dialectology. In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers).
[34] Yafeng Ren, Yue Zhang, Meishan Zhang, and Donghong Ji. 2016. Context-sensitive twitter sentiment classification using neural network. In AAAI, pages 215–221.
[35] Dominic Rout, Kalina Bontcheva, Daniel Preotu-Pietro, and Trevor Cohn. 2013. Where’s@ wally?: a classification approach to geolocating users based on their social ties. In Proceedings of the 24th ACM Conference on Hyperext and Social media.
[36] Aliaksei Seyrny and Alessandro Moschitti. 2015. Twitter sentiment analysis with deep convolutional neural networks. In Proceedings of the 38th International ACM SIGIR Conference on Research and Development in Information Retrieval, pages 959–962. ACM.
[37] Kai Sheng Tai, Richard Socher, and Christopher D Manning. 2015. Improved semantic representations from tree-structured long-term memory networks. In In proc. of ACL.
[38] Kristina Toutanova, Dan Klein, Christopher D Manning, and Yoram Singer. 2003. Feature-rich part-of-speech tagging with a cyclic dependency network. In Proceedings of the 2003 Conference of the North American Chapter of the Association for Computational Linguistics on Human Language Technology-Volume 1, pages 173–180. Association for Computational Linguistics.
[39] Dani Yogatama and Noah Smith. 2014. Making the most of bag of words: Sentence regularization with alternating direction method of multipliers. In Proc. of ACL.
[40] Quan Yuan, Gao Cong, Kaiqi Zhao, Zongyang Ma, and Aixin Sun. 2015. Who, what, when, and what: A nonparametric bayesian approach to context-aware recommendation and search for twitter users. ACM Transactions on Information Systems (TOIS), 33(1):2.
[41] Xiang Zhang, Junbo Zhao, and Yann LeCun. 2015. Character-level convolutional networks for text classification. In Advances in neural information processing systems, pages 649–657.
[42] Yiftah Ziser and Roi Reichart. 2017. Neural structural correspondence learning for geolocation and lexical dialectology. In Proceedings of the 21st annual international ACM SIGIR conference on Research and development in information retrieval, pages 959–962. ACM.