Introduction

Topic models are widely used in studying social phenomena. We conduct a comparative study examining state-of-the-art neural versus non-neural topic models, performing a rigorous quantitative and qualitative assessment on a dataset of tweets about the COVID-19 pandemic. Our results show that not only do neural topic models outperform their classical counterparts on standard evaluation metrics, they also produce more coherent topics, which are of great benefit when studying complex social problems. We also propose a novel regularization term for neural topic models, which is designed to address the well-documented problem of mode collapse, and demonstrate its effectiveness.

Related Work

There is a rich history of work on topic modelling, dating back to seminal works such as probabilistic Latent Semantic Analysis (pLSA) (Hofmann 1999), and Latent Dirichlet Allocation (LDA) (Blei, Ng, and Jordan 2003). In particular, LDA has proven to be a popular topic model, since it provides a full generative model that allows the topic distribution of unseen documents to be inferred. Since then, there has been a long line of work on constructing different “LDA-like” topic models, which modify this standard approach, for example by automatically learning the number of topics to use (Teh et al. 2006), modelling how topics change over time (Blei and Lafferty 2006), modelling class labels (McCallum and Jordan 2003), and modelling document metadata or other structural information (Mimno and McCallum 2012; Lee, Song et al. 2020), modelling structure between topics (Griffiths et al. 2004; Titov and McDonald 2008). As discussed earlier, recently, topic models using neural approaches have also been proposed (Miao, Grefenstette, and Blunsom 2017; Dieng, Ruiz, and Blei 2020). In addition, there is a line of work that studies different approaches for fitting such topic models. Originally, Blei, Ng, and Jordan (2003) proposed to fit their model using mean field variational inference. However, since then other approaches have been suggested that
have more appealing properties, such as collapsed Gibbs sampling (Griffiths and Steyvers 2004), which has the advantage of very accurate parameter estimation and inference, or variational inference based on variational autoencoding (Kingma and Welling 2013; Srivastava and Sutton 2014), which has the advantage of allowing instant inference of unseen documents without further training.

LDA, and LDA-like methods have been applied widely in textual analysis. However, when the corpora are comprised of a large number of short documents such as social media posts, and tweets, these methods are limited (Aldous, An, and Jansen 2019). Social scientists, who are trained in discourse analysis, and pay attention to linguistic nuances, have also pointed out that these off-the-shelf methods can only serve as shallow reading of the data, and are not sufficient when the goal is to produce fine-grained analysis. Methods like ETM (Aldous 2016), which has the advantage of allowing instant inference of unseen documents without further training.

Developing topic models that produce topics with high coherence and coverage is, therefore, an important task.

**Topic Modelling Methodology**

In this section, we describe our base topic models: Hierarchical Dirichlet Process (HDP) and Embedded Topic Model (ETM). Each of these methods takes some vocabulary \( \mathcal{V} \) (of size \( V \)) and a text collection over this vocabulary as input, and returns a topic model which is given by a tuple \((T, \text{infer})\), where \( T = \{T_1, T_2, \ldots, T_K\} \) is a set of \( K \) topics, with each topic defined by a distribution over \( \mathcal{V} \), and \( \text{infer} \) is a function that takes a document as input and returns a distribution over \( T \), which define the inferred topic weights for that document. Note that \( K \) may be either fixed as a hyperparameter, or learnt by the topic model.

**HDP.** Hierarchical Dirichlet Process (Teh et al. 2006) is a topic model based on a generative model for a text collection, which automatically learns the value of \( K \). Formally, the generative model is based on a hierarchy of Dirichlet processes (Ferguson 1973), which is a stochastic process parameterized by a base distribution and concentration parameter, whose sample paths are given by discrete probability distributions over the support of the base distribution. Specifically, it generates the set of topics \( T \) according to a top-level Dirichlet Process whose base distribution is a Dirichlet distribution over the vocabulary, and then independently generates each document according to a Dirichlet Process whose base distribution is given by the mixture of topics generated by the top-level Dirichlet process. This model is fit by collapsed Gibbs sampling (Griffiths and Steyvers 2004), with updates calculated based on the Chinese restaurant process (Aldous 1985) to ensure that the inferred topic weights are non-negative.

**ETM.** Embedded Topic Model (Dieng, Ruiz, and Blei 2020) is a topic model based on a low-rank approximation of the Latent Dirichlet Allocation (LDA) topic model, replacing the Dirichlet prior for the document-topic distributions with a Logistic Gaussian (Atchison and Steel 1980) prior in order to facilitate efficient training using variational autoencoders (Kingma and Welling 2013). Specifically, let \( \beta \in \mathbb{R}^{K \times V} \) denote the topic-word probability matrix, whose \((i,j)\)th entry denotes the probability of the \( j \)th word in \( V \) in topic \( T_i \). The ETM model parameterizes this matrix according to \( \beta = \text{softmax}(tv^T) \), where \( t \in \mathbb{R}^{K \times H} \) is a matrix of topic embeddings, \( v \in \mathbb{R}^{V \times H} \) is a matrix of word embeddings, and the hyperparameter \( H \) is the embedding dimension. The embeddings matrices \( v \) and \( t \) are fit using a variational autoencoder algorithm following Srivastava and Sutton (2014), which works by maximizing a lower bound for the log likelihood of the training data known as the Evidence Lower BOund (ELBO). The set of topics \( T \) is then given by these embedding matrices. Note that, unlike HDP, the number of topics \( K \) is not automatically inferred, and must be set as a hyperparameter. This variational autoencoder algorithm involves also fitting a neural network \( q \) which maps a document to a probability distribution over topics, which at convergence maps a document to its posterior distribution over topics, given the other model parameters \( v \) and \( t \). Therefore, we can implement the \( \text{infer} \) function by simply applying the fitted neural network \( q \) to the input document.

**Word2vec Pretraining** (Dieng, Ruiz, and Blei 2020) also proposed a variation of this model, where the word-embedding matrix was initialized using word2vec embeddings trained on the dataset. In our implementation of this variation, we use the Word2Vec implementation provided by Gensim (Rehurek and Sojka 2010), and continue to fine-tune word embeddings while training the topic model. Note that we do not use any external datasets to train our word embeddings. We call this model ETM+W2V.

**Topic Diversity Regularization.** A known challenge of generative models such as ETM that are trained via variational autoencoders is *mode collapse*, where the fitted model maps different topics to very similar distributions over words, which occurs due to bad local minima. To avoid this, we propose a diversity regularization term \( J(\beta) \), which we define according to

\[
J(\beta) = \frac{1}{|\pi|} \sum_{1 \leq i \leq K} \text{TV}(\beta_i, \beta_{\pi(i)}) ,
\]

where \( \beta_i \) denotes the \( i \)th row of \( \beta \), which corresponds to topic \( T_i \), \( \text{TV} \) denotes total variation distance, \( \pi \) is a random permutation of \( \{1, 2, \ldots, K\} \), and \(|\pi| = \sum_{1 \leq i \leq K} 1\{i \neq \pi(i)\} \). We regularize the ETM model by adding the term \( \lambda J(\beta) \) to the ELBO objective to be maximized, where \( \lambda \geq 0 \) is a hyperparameter controlling the strength of this regularization. We refer to the model that uses this regularization as ETM+W2V+TD.
COVID-19 Twitter Data

We study topic modeling on a dataset of tweets about the COVID-19 pandemic, provided by Chen, Lerman, and Ferrara (2020). For computational reasons, we limit the scope of our study to 99 days of data from January 22, 2020 to April 30, 2020. These 99 days include discussion of the early to mid stages of the COVID-19 pandemic, spanning the time from when COVID-19 was mostly limited to China to when it became a global pandemic. For this purpose, we believe the study of this period will provide crucial insights into public commentary of the pandemic.

Preprocessing. Our corpus consists of 15,156,897 tweets written by 5,049,470 users. For each day in our corpus, we sampled 10,000 tweets without replacement. We sampled 10% of tweets without replacement from the dataset to be used as a held-out test set for evaluation, and the remaining tweets (train split) were used for training the model.

For all tweets in each split, we performed the following sequence of preprocessing splits: (1) lower case the text; (2) tokenize tweet using the NLTK Twitter Tokenizer; (3) lemmatize each token using NLTK WordNet-based lemmatizer; (4) filter out every token with less than 3 characters; (5) filter out all stop words. Finally, we removed any tweets which has no tokens left after these steps. We report aggregate statistics for the processed dataset in Table 1.

Quantitative Experiments

First we describe our quantitative experiments on the COVID-19 Twitter Dataset. For these experiments, we compare the previously described topic models using several automated or human evaluation metrics, described below.

Evaluation Metrics

Perplexity (Perp): this metric is computed according to $\exp(-\ln(L)/n_{tok})$, where $\ln(L)$ is the estimated log likelihood of the held-out test data according to the given topic model, and $n_{tok}$ is the total number of tokens in the test data. This is based on the assumption that a good topic model will predict a high likelihood for held-out documents, and therefore will have low perplexity.

Coherence (Coh): For any given words $w$ and $w'$, let $P_{test}(w)$ and $P_{test}(w, w')$ respectively denote the probability of $w$ appearing in a randomly sampled test document, and the probability of $w$ and $w'$ co-occurring in a randomly sampled test document, and let $\text{npmi}(w, w')$ denote the normalized pointwise mutual information between $w$ and $w'$, defined according to

$$\text{npmi}(w, w') = \frac{\log \frac{P_{test}(w)P_{test}(w, w')}{P_{test}(w')}}{-\log P_{test}(w, w')}.$$

In addition, let $w_j^{(k)}$ be the $i$'th highest-probability word in the $k$'th topic. Then, the coherence metric is calculated according to $\frac{1}{K} \sum_{k=1}^{K} \frac{1}{10} \sum_{i=1}^{10} \sum_{j=i+1}^{10} \text{npmi}(w_i^{(k)}, w_j^{(k)})$, where $K$ is the number of topics. This is based on the assumption that the top words of a topic should co-occur often, and therefore a good topic model will have high coherence.

Topic Gap (TG): This metric measures diversity between different topics. To compute this, we take the union of top 10 highest-probability words from each of the $K$ topics, and compute the metric according to $n_{unique}/10K$, where $n_{unique}$ is the number of unique words in this union. If each topic generates a disjoint set of top 10 words, then the topic gap will have a maximum value of 1. A higher value, denotes less repetitive topics, which is a desirable property.

Human Evaluation (CS): This metric is motivated by past work on topic and word intrusion tests (Chang et al. 2009; Schnabel et al. 2015). We used the following setup for our human study: annotators were provided with pairs of word lists, each containing five words sampled from the same topic. To generate these lists, we first sample a topic $k$ from its prior probability. Then, we uniformly sample 5 words from the set of top 10 highest probability words for this topic, and create our first list $U_1$ using them. With 50% probability, we use the remaining five words as the second list $U_2$. Otherwise, we randomly sample a different topic $l$, and we create the list $U_2$ by uniformly sampling 5 words from $l$’s top 10 highest probability words (after removing words in $U_1$). Annotators were then asked to predict whether $U_1$ and $U_2$ were sampled from the same or different topics. For each method, we annotated 100 such pairs in total. For all methods, we then calculated a contrast score, which we define as the fraction of correct annotations for that method. Ideally, this metric should capture similar information to the automated coherence and topic gap metrics, since in order for correct annotation to be possible the top words in each topic must be at least somewhat cohesive and distinct from the top words in other topics. However, unlike these automated metrics it has the advantage that it can leverage linguistic intuitions.

Table 1: Statistics for the preprocessed Covid-19 dataset containing tweets between Jan 22nd, 2020 and April 30th, 2020.

| Dataset Statistics          | Values          |
|-----------------------------|-----------------|
| Number of train tweets      | 874,975         |
| Number of test tweets       | 10,000          |
| Number of users             | 5,049,470       |
| Vocabulary size             | 21,471          |
| Number of tokens per tweet  | 8.86            |
metrics than vice versa.

In the case of HDP, we used the tomotopy implementation. We speculate that this may be due to the low-rank factorization of the topic-word distribution employed by neural models and may help prevent over-fitting. The base model ETM, however, suffers from mode collapse and does not generate a diverse set of topics. It also receives the lowest contrast score, indicating that the annotators were unable to differentiate topics. Using word2vec initialization (ETM + W2V) significantly improves all four metrics. However, the topic gap remains below HDP. Lastly, our proposed variant ETM + W2V + TD outperforms other models on most metrics, and in particular, achieves the highest human evaluation score.

**Topic Analysis of COVID-19 Twitter Data**

We finally present our qualitative analysis, using the topics produced by our HDP and ETM topic models on the COVID-19 Twitter dataset. The goals of this analysis are twofold: we wish to understand the topical trends in this data, as well as compare the extent to which we can perform such analysis with our different topic models. At an high level, our analysis proceeds as follows: (1) we run our best-performing HDP and ETM topic models from the previous experiments on the dataset; (2) we extract the topics from these, and cluster them into 11 meta-topics, each with multiple sub-topics; and (3) we calculate the prevalence of these meta-topics over time according to our two topic models.

Based on our analysis of the topics produced by these models, we decided on the following meta-topics: (1) China; (2) Economic Impact; (3) Social Impact; (4) Politics; (5) Individual Containment Measures; (6) Administrative Response; (7) Frustration and Anger; (8) Hospitals and Healthcare; (9) Pandemic News Updates; (10) Information about the Virus; and (11) Misinformation. In addition, we used an additional Miscellaneous meta-topic for any tweet that did not fit into our core meta-topics. Sub-topics contain finer information. For example, fear, prayer, and frustration.

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**Implementation Details.** In the case of HDP, we used the tomotopy implementation. We trained the model for 4,000 iterations, and evaluated it every 100 iterations. For ETM, we used the code provided by the authors. We trained the model for 100 epochs using batch sizes of 1000, and evaluated every 2,500 iterations. For every experiment, we use perplexity on the test set to select model.

For all methods, we performed grid search over hyperparameters. For HDP, this included the three hyperparameters ($\alpha$, $\beta$, $\eta$) that control the Dirichlet processes, and for ETM, it included number of topics, learning rate, hidden dimension, all word2vec hyperparameters, and the weight of topic diversity regularizer. We selected the best hyperparameters using the three automated metrics.

**Results.** We report performance of topic models in Table 2. We observe that HDP generates reasonably diverse topics, but these topics lack coherence and have high perplexity on held-out test data. In comparison, all ETM models achieve significantly lower perplexity and higher coherence. We speculate that this may be due to the low-rank factorization of the topic-word distribution employed by neural topic models, which reduces the effective number of parameters and may help prevent over-fitting. The base model ETM, however, suffers from mode collapse and does not generate a diverse set of topics. It also receives the lowest contrast score, indicating that the annotators were unable to differentiate topics. Using word2vec initialization (ETM + W2V) significantly improves all four metrics. However, the topic gap remains below HDP. Lastly, our proposed variant ETM + W2V + TD outperforms other models on most metrics, and in particular, achieves the highest human evaluation score.

**Table 2: Performance of topic models on different metrics.**

| Topic Model | Perp | Coh | TG | CS |
|-------------|------|-----|----|----|
| HDP         | 78/75.4 | 0.03 | 0.39 | 0.81 |
| ETM         | 2831.1  | 0.05 | 0.12 | 0.73 |
| ETM + W2V   | 2754.9  | 0.11 | 0.21 | 0.86 |
| ETM + W2V + TD | 2312.5 | 0.09 | 0.55 | 0.88 |

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*This was done by considering all metrics, with hyperparameter configuration $A$ preferred over $B$ if $A$ outperformed $B$ on more metrics than vice versa.

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*https://bab2min.github.io/tomatopy/

*https://github.com/adjidieng/ETM

*This was done based on the topics’ top words, and by “deep reading” 50 exemplar tweets per topic (Nelson 2020).
with administration are sub-topics of the meta-topic frustration.

First, we plot the prevalence over time of five of these meta-topics in Figure 1 for both our HDP and the best ETM model. We can see here that in most cases, the general trend of HDP and ETM agree with each other. For example, for the meta-topics in Figure 1, for both our HDP and the best ETM model. We can see here that in most cases, the general trend of HDP and ETM agree with each other. For example, for the meta-topics of "administration" and "meta-topics", we can see that the general trend for both HDP and ETM is similar. However, in some cases, such as "political response", the trends are very different.

Table 3: We present the top 10 words for 5 randomly sampled topics falling under two different meta-topics, for our different topic-modelling methods.

| Politics     | Social Impact                                      |
|--------------|---------------------------------------------------|
| HDP          |                                                   |
| china, coronavirus, #coronavirus, chinese, outbreak, minister, covid, president, health, fight | coronavirus, covid, church, lockdown, #coronavirus, service, pastor, china, pandemic, #covid19 |
| coronavirus, vote, election, trump, pandemic, biden, covid, bernie, voting, voter | corona, coronavirus, virus, china, covid, cancelled, due, outbreak, hope, week |
| coronavirus, Boris, lockdown, Johnson, covid, government, #coronavirus, minister, news, #covid19 | coronavirus, league, game, china, covid, player, season, corona, football, team |
| china, trump, money, deal, trade, biden, american, coronavirus, billion, ukraine | covid, coronavirus, #covid19, service, home, lockdown, #coronavirus, pandemic, stay, due |
| ETM + W2V    |                                                   |
| trump, president, democrat, vote, election, republican, penny, hoax, donald, biden | school, coronavirus, student, covid, class, online, university, home, #coronavirus, china |
| trump, american, medium, fact, lie, truth, president, racist, cdc, blame | event, cancel, cancelled, due, canceled, sport, 2020, postponed, player, league |
| 2020, march, april, feb, february, jan, january, refund, ticket, due | school, close, area, order, open, student, closed, city, border, shut |
| china, country, chinese, america, war, usa, deal, trade, power, citizen | #stayhome, #stayathome, #lockdown, #staysafe, #socialdistancing, #quarantine, #covid19, #quarantinelife, #stayhomelives, #corona |
| china, chinese, country, communist, usa, america, war, party, russia, ccp | covid, lockdown, week, home, family, due, place, month, call, today |
| ETM + W2V + TD |                                                   |
| house, county, white, governor, gov, biden, california, florida, york, donald | due, event, game, cancelled, cancel, concern, trip, postponed, ticket, fan |
| government, law, act, action, policy, federal, court, failed, legal, nigerian | pandemic, crisis, plan, working, fight, part, community, response, team, hard |
| trump, president, american, america, democrat, lie, administration, vote, blame, obama | family, friend, love, hope, guy, feel, happy, message, kind, hey |
| health, public, official, emergency, national, minister, organization, general, authority, security | week, today, school, due, order, lockdown, hour, class, move, return |
| party, war, communist, power, ccp, police, political, mass, china’s, protest | city, quarantine, place, close, open, shut, area, border, closed, local |

Table 3: We present the top 10 words for 5 randomly sampled topics falling under two different meta-topics, for our different topic-modelling methods.
Conclusion

Our study suggests that neural topic modeling is beneficial for studying complex social issues. While some argue that topic modeling in social science can only serve as the first level of shallow human coding, our research shows that with the new development of neural topic modeling, analysts can extract more interpretable and richer categories from their corpora.

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Reproducibility. Code for reproducing our results can be found at https://github.com/ngathan/etm-covid-analysis. Please see Chen, Lerman, and Ferrara (2020) for information about the dataset.

References

Abebe, R.; Hill, S.; Vaughan, J. W.; Small, P. M.; and Schwartz, H. A. 2019. Using search queries to understand health information needs in africa. In Proceedings of the International AAAI Conference on Web and Social Media, volume 13, 3–14.

Aldous, D. J. 1985. Exchangeability and related topics. In École d’Été de Probabilités de Saint-Flour XIII—1983, 1–198. Springer.

Aldous, K. K.; An, J.; and Jansen, B. J. 2019. View, like, comment, post: Analyzing user engagement by topic at 4 levels across 5 social media platforms for 53 news organizations. In Proceedings of the International AAAI Conference on Web and Social Media, volume 13, 47–57.

Atchison, J.; and Shen, S. M. 1980. Logistic-normal distributions: Some properties and uses. Biometrika 67(2): 261–272.

Blei, D. M.; and Lafferty, J. D. 2006. Dynamic topic models. In Proceedings of the 23rd international conference on Machine learning, 113–120.

Blei, D. M.; Ng, A. Y.; and Jordan, M. I. 2003. Latent dirichlet allocation. Journal of machine Learning research 3(Jan): 993–1022.

Chang, J.; Gerrish, S.; Wang, C.; Boyd-Graber, J.; and Blei, D. 2009. Reading tea leaves: How humans interpret topic models. Advances in neural information processing systems 22: 288–296.

Chen, E.; Lerman, K.; and Ferrara, E. 2020. Tracking Social Media Discourse About the COVID-19 Pandemic: Development of a Public Coronavirus Twitter Data Set. JMIR Public Health and Surveillance 6(2): e19273.

Dieng, A. B.; Ruiz, F. J.; and Blei, D. M. 2020. Topic modeling in embedding spaces. Transactions of the Association for Computational Linguistics 8: 439–453.

DiMaggio, P.; Nag, M.; and Blei, D. 2013. Exploiting affinities between topic modeling and the sociological perspective on culture: Application to newspaper coverage of US government arts funding. Poetics 41(6): 570–606.

Ferguson, T. S. 1973. A Bayesian analysis of some nonparametric problems. The annals of statistics 209–230.

Griffiths, T. L.; Jordan, M. I.; Tenenbaum, J. B.; and Blei, D. M. 2004. Hierarchical topic models and the nested Chinese restaurant process. In Advances in neural information processing systems, 17–24.

Griffiths, T. L.; and Steyvers, M. 2004. Finding scientific topics. Proceedings of the National academy of Sciences 101(suppl 1): 5228–5235.

Hofmann, T. 1999. Probabilistic latent semantic indexing. In Proceedings of the 22nd annual international ACM SIGIR conference on Research and development in information retrieval, 50–57.

Kingma, D. P.; and Welling, M. 2013. Auto-encoding variational bayes. arXiv preprint arXiv:1312.6114.

Lee, M.; Song, M.; et al. 2020. Incorporating citation impact into analysis of research trends. Scientometrics 1–34.

Mcguliffe, J.; and Blei, D. 2007. Supervised topic models. Advances in neural information processing systems 20: 121–128.

Miao, Y.; Grefenstette, E.; and Blumsom, P. 2017. Discovering discrete latent topics with neural variational inference. arXiv preprint arXiv:1706.00359.

Minno, D.; and McCallum, A. 2012. Topic models conditioned on arbitrary features with dirichlet-multinomial regression. arXiv preprint arXiv:1206.3278.

Nelson, L. K. 2020. Computational grounded theory: A methodological framework. Sociological Methods & Research 49(1): 3–42.

Nelson, L. K.; Burk, D.; Knudsen, M.; and McCall, L. 2018. The future of coding: A comparison of hand-coding and three types of computer-assisted text analysis methods. Sociological Methods & Research 00491241118769114.

Ramage, D.; Manning, C. D.; and Dumais, S. 2011. Partially labeled topic models for interpretable text mining. In Proceedings of the 17th ACM SIGKDD international conference on Knowledge discovery and data mining, 457–465.

Řehůřek, R.; and Sojka, P. 2010. Software Framework for Topic Modelling with Large Corpora. In Proceedings of the LREC 2010 Workshop on New Challenges for NLP Frameworks, 45–50. Valletta, Malta: ELRA.

Roberts, M. E.; Stewart, B. M.; Tingley, D.; Airoldi, E. M.; et al. 2013. The structural topic model and applied social science. In Advances in neural information processing systems workshop on topic models: computation, application, and evaluation, volume 4. Harrahs and Harveys, Lake Tahoe.
Rodriguez, M. Y.; and Storer, H. 2020. A computational social science perspective on qualitative data exploration: Using topic models for the descriptive analysis of social media data. *Journal of Technology in Human Services* 38(1): 54–86.

Schnabel, T.; Labutov, I.; Mimno, D.; and Joachims, T. 2015. Evaluation methods for unsupervised word embeddings. In *Proceedings of the 2015 conference on empirical methods in natural language processing*, 298–307.

Srivastava, A.; and Sutton, C. 2016. Neural variational inference for topic models. In *Bayesian deep learning workshop, NIPS*, volume 2016.

Teh, Y. W.; Jordan, M. I.; Beal, M. J.; and Blei, D. M. 2006. Hierarchical dirichlet processes. *Journal of the american statistical association* 101(476): 1566–1581.

Titov, I.; and McDonald, R. 2008. Modeling online reviews with multi-grain topic models. In *Proceedings of the 17th international conference on World Wide Web*, 111–120.