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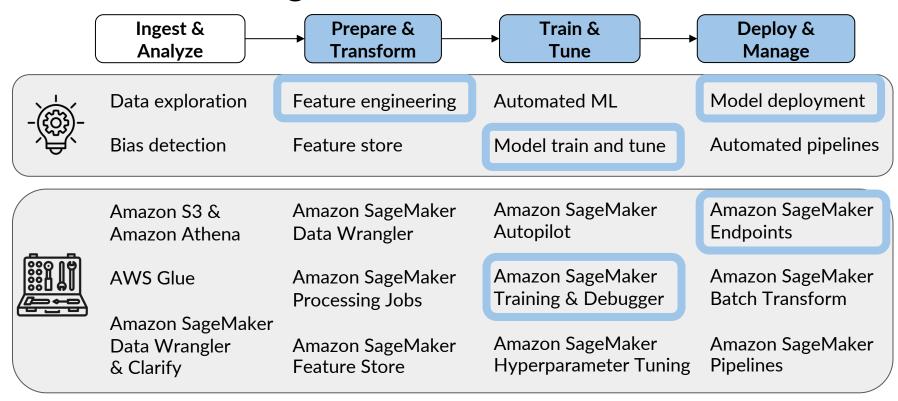




Practical Data Science

Built-In Algorithms

Machine Learning Workflow





Why use built-in algorithms?

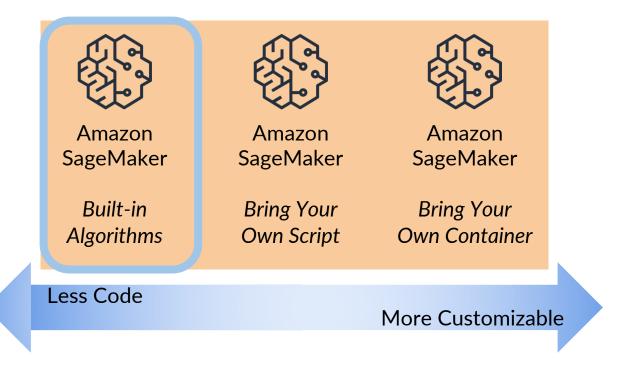
- Implementations are highly-optimized and scalable
- Focus more on domain-specific tasks rather than managing low-level model code and infrastructure



Trained model can be downloaded and re-used elsewhere



When to choose built-in algorithms vs. custom code



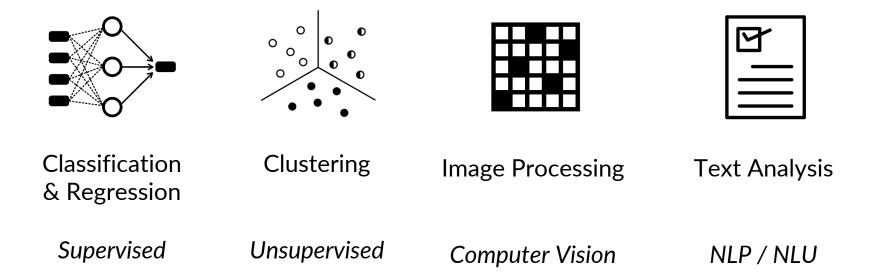


Use cases and algorithms





Popular ML tasks and learning paradigms





Classification & regression

| Example problems and use cases | Problem types | Input format | Built-in algorithms |
|--|-----------------------------------|-----------------|--|
| Predict if an item belongs to a category: an email spam filter | Binary/multi-class classification | Tabula r | XGBoost, K-Nearest Neighbors (k-NN) |

Classification & regression

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| Predict a numeric/continuous value: estimate the value of a house | Regression | Tabula r | Linear Learner, XGBoost |



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| Predict sales on a new product based on previous sales data | Time-series forecasting | Tabula r | DeepAR Forecasting |



| Example problems and use cases | Problem types | Input format | Built-in algorithms |
|--|--|-----------------|------------------------------------|
| Drop weak features such as the color of a car when predicting its mileage. | Feature engineering: reduce dimensions | Tabular | Principal Component Analysis (PCA) |



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| Group high/medium/low-spending customers from transaction histories | Clustering / grouping | Tabular | K-Means |
| Organize a set of documents into topics based on words and phrases | Topic modeling | Text | Latent Dirichlet Allocation (LDA), Neural Topic Model (NTM) |



Image processing

| Example problems and use cases | Problem types | Input format | Built-in algorithms |
|--------------------------------|----------------------|-----------------|----------------------|
| Content moderation | Image classification | Image | Image Classification |



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| Self-driving cars identify objects in their path | Computer vision | Image | Semantic Segmentation |



| Example problems and use cases | Problem types | Input format | Built-in algorithms |
|--------------------------------|---------------------|-----------------|----------------------|
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| Example problems and use cases | Problem types | Input format | Built-in algorithms |
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| Classify reviews into categories | Text classification | Text | BlazingText |







Evolution of text analysis algorithms

Word2Vec Jan 2013



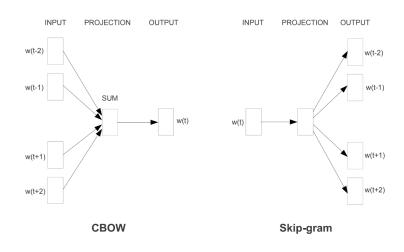
Text analysis algorithm - Word2Vec

Concepts

- Convert text into vectors called "embeddings"
- 300-dimensional vector space
- Perform machine learning on the vectors

Model architectures to create the embeddings

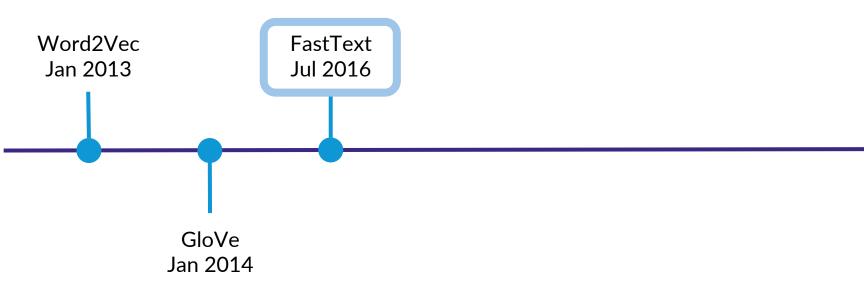
- Continuous bag-of-words (CBOW)
- Continuous skip-gram



Source: "Efficient Estimation of Word Representations in Vector Space", Mikolov et al., 2013



Evolution of text analysis algorithms





Text analysis algorithm - FastText

Concepts

- Extension of word2vec
- Breaks the word into character sets of length n (n-grams):
 "amazon" => "a", "am", "amaz", "amazo", "amazon"
- Embedding for a word is the aggregate of the embedding of each n-gram within the word

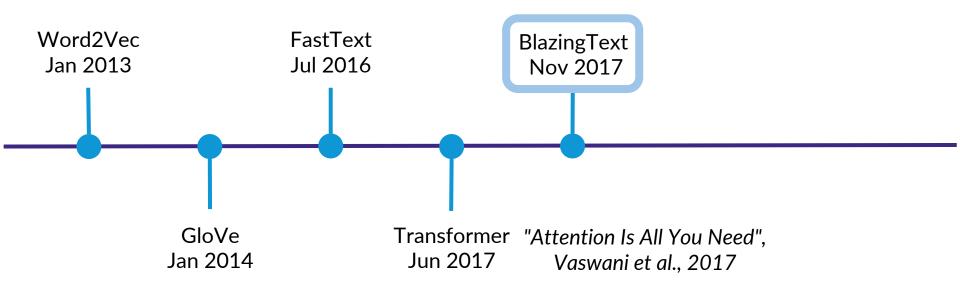
Implementation

- CBOW and skip-gram models
- Adds text classification

Helps with the out-ofvocabulary (OOV) issue with word2vec



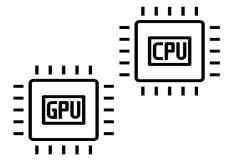
Evolution of text analysis algorithms





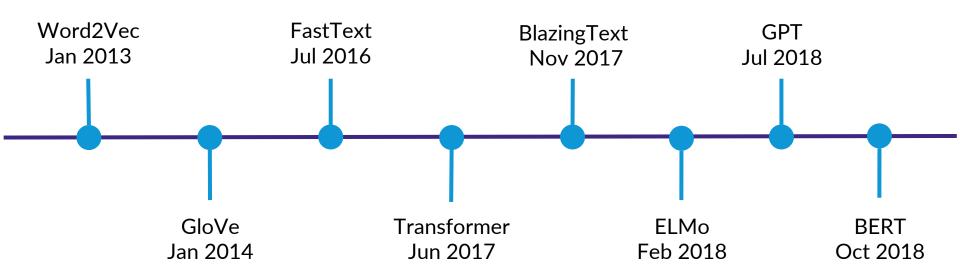
Text analysis algorithm - BlazingText

- Scales and accelerates Word2Vec using multiple CPUs or GPUs for training
- Extends FastText to use GPU acceleration with custom CUDA kernels
- Creates n-gram embeddings using CBOW and skip-gram
- Saves money by early-stopping a training job
 - when the validation accuracy stops increasing
- Optimized I/O for datasets stored in Amazon S3





Evolution of text analysis algorithms





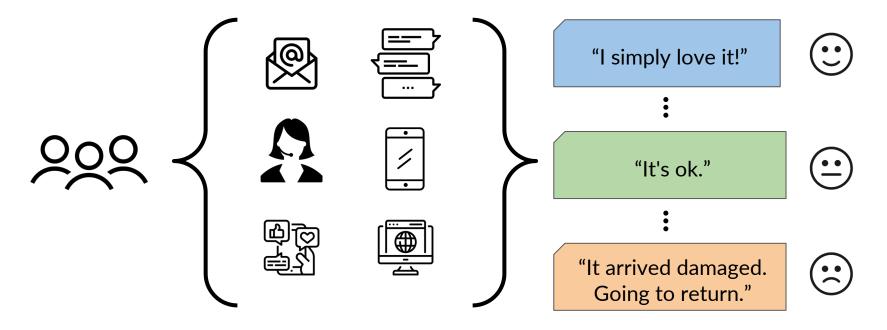
Train a text classifier

with Amazon SageMaker BlazingText



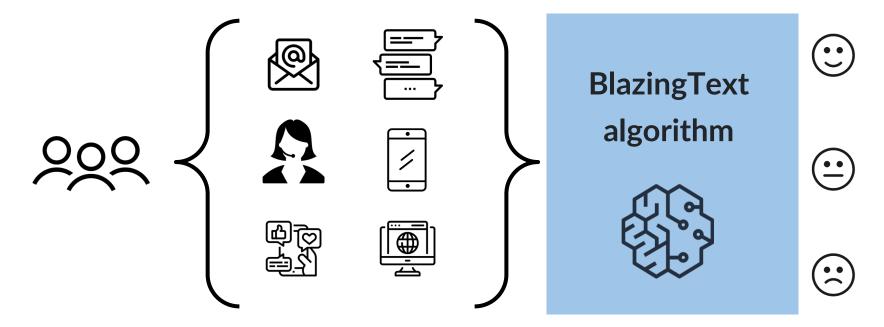


Multi-class classification for sentiment analysis of product reviews



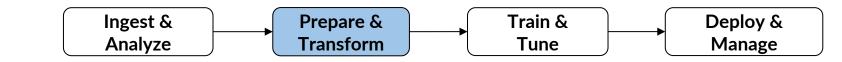


Multi-class classification for sentiment analysis of product reviews





Transform raw review data into features



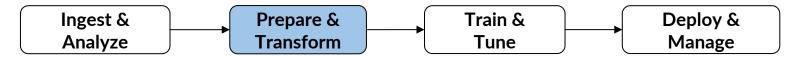
```
sentiment,review_body
1,"i simply love it"
0,"it's ok"
-1,"it arrived damaged. going to return"
```



```
__label__1 "i simply love it ."
__label__0 "it's ok ."
__label__-1 "it arrived damaged ."
```



Transform raw review data into features





```
def tokenize(review):
    return nltk.word_tokenize(review)
```



```
__label__1 "i simply love it ."
__label__0 "it's ok ."
__label__-1 "it arrived damaged, going to return ."
```







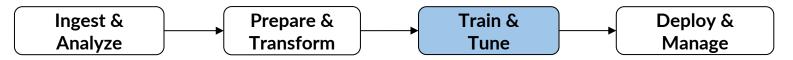


Amazon SageMaker BlazingText hyper-parameters for text classification

| Parameter Name | Recommended Ranges or Values | Description |
|----------------|---------------------------------|--|
| epochs | [5-15] | Number of complete passes through the dataset |
| learning_rate | [0.005-0.01] | Step size for the numerical optimizer |
| min_count | [0-100] | Discard words that appear less than this number |
| vector_dim | [32-300] | Number of dimensions in vector space |
| word_ngrams | [1-3] | Number of words n-gram features to use |
| early_stopping | True or False | Stop training if validation accuracy stops improving |
| patience | [5-15] | Number of epochs before early stopping |



Train a text classifier using Amazon SageMaker BlazingText



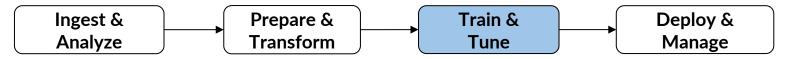
```
train_data = sagemaker.inputs.TrainingInput(...)
validation_data = sagemaker.inputs.TrainingInput(...)

data_channels = {
    'train': train_data,
    'validation': validation_data
}

image_uri = sagemaker.image_uris.retrieve(framework='blazingtext', ...)
Retrieves Amazon ECR image URIs for pre-built SageMaker Docker images.
```



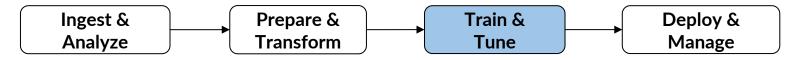
Train a text classifier using Amazon SageMaker BlazingText



```
train data = sagemaker.inputs.TrainingInput(...)
validation data = sagemaker.inputs.TrainingInput(...)
                                                         Retrieves Amazon ECR image URIs
data channels = {
                                                         for pre-built SageMaker Docker
    'train': train data,
                                                         images.
    'validation': validation data
image uri = sagemaker.image uris.retrieve(framework='blazingtext', ...)
estimator = sagemaker.estimator.Estimator(image uri=image uri, ...)
estimator.set hyperparameters(...)
estimator.fit(...)
```



Evaluate the classifier



| time | metric_name | value |
|------|---------------------|--------|
| 0.00 | train:accuracy | 0.4865 |
| 10.0 | train:accuracy | 0.5220 |
| 20.0 | validation:accuracy | 0.5364 |



and make predictions

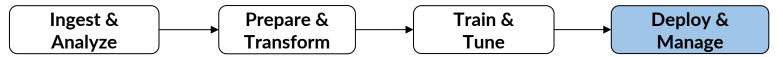






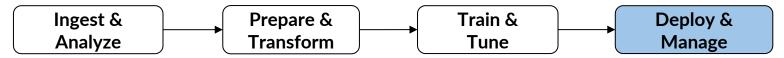
```
text classifier = estimator.deploy(
                                                       Increase instance_count > 1 to
    initial_instance_count=1,
                                                       easily scale out
    instance_type='ml.m4.xlarge', ...)
```





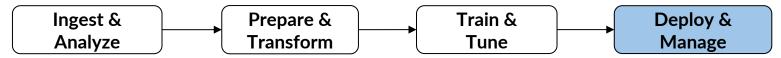
```
text classifier = estimator.deploy(
      initial instance count=1,
      instance type='ml.m4.xlarge', ...)
                                                                                   blazingtext-2020-12-07-21-45-06-296
                                                                                     Endpoint settings
                                                                                                                              Status
                                                                                       Name
                                                                                       blazingtext-2020-12-07-21-45-06-296
                                                                                                                              ARN
                                                                                                                              Creation time
                                                                                       arn:aws:sagemaker:us-east-
                                                                                                                              Mon Dec 07 2020 13:45:07 GMT-0800 (Pacific
                                                                                       1:835319576252:endpoint/blazingtext-2020-12-07-
                                                                                                                              Standard Time)
                                                                                       21-45-06-296
                                                                                                                              Last updated
                                                                                                                              Mon Dec 07 2020 13:51:23 GMT-0800 (Pacific
                                                                                                                              Standard Time)
```





```
text classifier = estimator.deploy(
    initial instance count=1,
    instance type='ml.m4.xlarge', ...)
payload = {'instances': ['This product is great']}
                                                            Sample prediction request
response = text_classifier.predict(...)
```





```
text classifier = estimator.deploy(
    initial instance count=1,
    instance type='ml.m4.xlarge', ...)
payload = {'instances': ['This product is great']}
                                                             Sample prediction request
response = text classifier.predict(...)
## Sample response:
[{
                                               Prediction response and
    "label": [" label 1"],
                                               probability score
    "prob": [0.9506041407585144]
}]
```

