Text Classification

Rob Minneker

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Administrivia

- Course website has some updates
- Noah Smith will give a guest lecture February 3rd, please attend in person!
- A1 will be released Thursday, plan ahead

Sources

Content derived from: J&M Ch. 4

Part 1: Foundations of Text Classification

Text classification assigns predefined categories to text using supervised learning. (1/5)

- Text classification assigns predefined categories to text using supervised learning.
  - Let x denote an input text (e.g., document, sentence), and y a discrete label.
  - The classification function $f_\theta(x) : \mathcal{X} \to \mathcal{Y}$ is learned from labeled data $\mathcal{D} = \{(x^{(i)}, y^{(i)})\}_{i=1}^{N}$.

Text classification assigns predefined categories to text using supervised learning. (2/5)

- For binary labels $y^{(i)} \in \{0, 1\}$, define $\hat{y}^{(i)} = p_\theta(y = 1 \mid x^{(i)})$.
- Bernoulli likelihood:

$$p_\theta(y^{(i)} \mid x^{(i)}) = \hat{y}^{(i)y^{(i)}}(1 - \hat{y}^{(i)})^{1-y^{(i)}}$$

- MLE maximizes the log-likelihood:

$$\hat{\theta}_{\mathrm{MLE}} = \arg\max_\theta \sum_{i=1}^{N} \log p_\theta(y^{(i)} \mid x^{(i)})$$

Text classification assigns predefined categories to text using supervised learning. (3/5)

- Negative log-likelihood gives cross-entropy:

$$\mathcal{L}(\theta) = -\sum_{i=1}^{N} \left[y^{(i)} \log \hat{y}^{(i)} + (1 - y^{(i)}) \log(1 - \hat{y}^{(i)}) \right]$$

- Empirical risk is the average loss:

$$\hat{\theta} = \arg\min_{\theta} \frac{1}{N} \sum_{i=1}^{N} \mathcal{L}^{(i)} = \arg\min_{\theta} \hat{R}_n(\theta)$$

- Multiclass generalization uses softmax cross-entropy ($-\log \hat{y}_y$).

Text classification assigns predefined categories to text using supervised learning. (4/5)

- Tasks include binary, multiclass, and multilabel classification (e.g., spam detection, sentiment analysis).
  - **Binary:** $\mathcal{Y} = \{0, 1\}$ (e.g., spam vs. not spam)
  - **Multiclass:** $\mathcal{Y} = \{1, \ldots, K\}$ (e.g., topic labeling with K classes)
  - **Multilabel:** $\mathcal{Y} \subseteq \{1, \ldots, K\}$ (e.g., documents tagged with multiple topics)
  - The choice impacts the loss function: sigmoid for binary, softmax for multiclass, sigmoid per label for multilabel.

Binary, multiclass, multilabel: outputs and loss

Binary

```
Email → Spam?
        0/1
```

- Output: $\hat{y} = \sigma(z)$
- Loss: $-\left[y \log \hat{y} + (1 - y) \log(1 - \hat{y})\right]$

Multiclass

```
Doc → Topic
      {1..K}
```

- Output: $\hat{y}_k = \mathrm{softmax}(z)_k$
- Loss: $-\log \hat{y}_y$

Multilabel

```
Doc → Tags
      {0,1}^K
```

- Output: $\hat{y}_k = \sigma(z_k)$
- Loss: $-\sum_k \left[y_k \log \hat{y}_k + (1 - y_k) \log(1 - \hat{y}_k)\right]$

Text classification assigns predefined categories to text using supervised learning. (5/5)

- Clear problem formulation enables effective model selection and evaluation in NLP applications.
  - Precise definition of input/output space $(\mathcal{X}, \mathcal{Y})$ guides feature engineering and architecture.
  - Evaluation metrics (accuracy, F1, AUC) depend on task structure.

Applications:

- Spam filtering (binary)
- Sentiment analysis (binary/multiclass)
- News categorization (multiclass)
- Multi-topic assignment (multilabel)

Text data is represented as feature vectors using models like Bag-of-Words and TF/IDF. (1/3)

- Text data is represented as feature vectors using models like Bag-of-Words and TF/IDF.
- Bag-of-Words (BoW) encodes a document as a sparse vector of term counts.
  - Given vocabulary $V = \{w_1, \ldots, w_{|V|}\}$, a document d is represented as

$$\mathbf{x}_d = [c(w_1, d), c(w_2, d), \ldots, c(w_{|V|}, d)]$$

where $c(w_i, d)$ is the count of word w_i in d.

- Ignores word order, capturing only term presence and frequency.

Toy Bag-of-Words example

- Corpus sentence:
  - "The quick brown fox jumped over the quick, lazy sheep dog."
- Lowercase + split into tokens, then count each word.

Word	**Count**
the	2
quick	2
brown	1
fox	1
jumped	1
over	1
lazy	1
sheep	1
dog	1

- Encode a new sentence with the same vocabulary:
  - "The quick orange fox, jumped over the lazy, slow turtle."
  - Vocabulary order: the, quick, brown, fox, jumped, over, lazy, sheep, dog
  - Encoded vector: [2, 1, 0, 1, 1, 1, 1, 0, 0]
  - Out-of-vocabulary words are ignored: orange, slow, turtle

Text data is represented as feature vectors using models like Bag-of-Words and TF/IDF. (2/3)

- Term Frequency-Inverse Document Frequency (TF/IDF) re-weights terms to emphasize discriminative words.
  - For term t in document d:

$$\text{tfidf}(t, d) = \text{tf}(t, d) \cdot \text{idf}(t)$$

where $\text{tf}(t, d) = \frac{c(t,d)}{\sum_{t'} c(t',d)}$ and $\text{idf}(t) = \log \frac{N}{n_t}$ with N total documents and n_t documents containing t.

Toy TF/IDF example with 3 documents

Documents:

- d_1: "apple banana apple"
- d_2: "banana carrot"
- d_3: "apple carrot carrot"

Vocabulary: $\{\text{apple}, \text{banana}, \text{carrot}\}$, $N = 3$.

Document frequencies: $n_{\text{apple}} = 2$, $n_{\text{banana}} = 2$, $n_{\text{carrot}} = 2$.

So $\text{idf}(\cdot) = \log \frac{3}{2}$ for all three terms.

Example TF/IDF:

- For term "apple" in d_1: $\text{tf} = \frac{2}{3}$, so $\text{tfidf} = \frac{2}{3} \log \frac{3}{2}$.
- For term "carrot" in d_2: $\text{tf} = \frac{1}{2}$, so $\text{tfidf} = \frac{1}{2} \log \frac{3}{2}$.

From TF/IDF to feature vectors

Fix vocabulary order: $\left[\text{apple}, \ \text{banana}, \ \text{carrot}\right]$.

TF vectors:

- d_1: $\left[\frac{2}{3}, \ \frac{1}{3}, \ 0\right]$
- d_2: $\left[0, \ \frac{1}{2}, \ \frac{1}{2}\right]$
- d_3: $\left[\frac{1}{3}, \ 0, \ \frac{2}{3}\right]$

Since $\text{idf} = \log \frac{3}{2}$ for every term, TF/IDF feature vectors are:

- $v_1 = \left[\frac{2}{3}\log \frac{3}{2}, \ \frac{1}{3}\log \frac{3}{2}, \ 0\right]$
- $v_2 = \left[0, \ \frac{1}{2}\log \frac{3}{2}, \ \frac{1}{2}\log \frac{3}{2}\right]$
- $v_3 = \left[\frac{1}{3}\log \frac{3}{2}, \ 0, \ \frac{2}{3}\log \frac{3}{2}\right]$

These vectors are the rows of the TF/IDF feature matrix for the corpus.

Text data is represented as feature vectors using models like Bag-of-Words and TF/IDF. (3/3)

- Applications of TF/IDF:
  - Enables use of linear models (e.g., logistic regression, SVMs) for text classification.
  - Forms the basis for feature selection and further dimensionality reduction.

Evaluation metrics like accuracy, precision, recall, and F1-score measure classifier performance. (1/8)

- Evaluation metrics like accuracy, precision, recall, and F1-score measure classifier performance.
- Accuracy quantifies overall correctness:

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN}$$

where TP = true positives, TN = true negatives, FP = false positives, FN = false negatives.

Spam dataset: Is this a good model?

- Suppose 1,000,000 emails: 999,000 ham (99.9%) and 1,000 spam (0.1%).
- A model predicts **ham** for every message.
- Accuracy = 999,000 / 1,000,000 = **99.9%**.
- Is this a good model?

Evaluation metrics like accuracy, precision, recall, and F1-score measure classifier performance. (2/8)

- Precision and recall are class-specific:

$$\text{Precision} = \frac{TP}{TP + FP} \qquad \text{Recall} = \frac{TP}{TP + FN}$$

- Precision: proportion of predicted positives that are correct.
- Recall: proportion of actual positives that are retrieved.

Evaluation metrics like accuracy, precision, recall, and F1-score measure classifier performance. (3/8)

- F1-score balances precision and recall:

$$F_1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

- Generalizes to F_β for weighting recall vs. precision.

> **Note**
>
> **F_β formula:**
>
> $$F_\beta = (1 + \beta^2) \cdot \frac{\text{Precision} \cdot \text{Recall}}{(\beta^2 \cdot \text{Precision}) + \text{Recall}}$$

Evaluation metrics like accuracy, precision, recall, and F1-score measure classifier performance. (4/8)

- The confusion matrix summarizes true/false positives/negatives; F1 balances precision and recall.
- The confusion matrix structure:

	Predicted +	Predicted −
Actual +	TP	FN
Actual −	FP	TN

Evaluation metrics like accuracy, precision, recall, and F1-score measure classifier performance. (5/8)

Evaluation metrics like accuracy, precision, recall, and F1-score measure classifier performance. (6/8)

- Directly visualizes classifier errors and successes.
  - Precision-Recall tradeoff:
  - High precision, low recall: conservative classifier.
  - High recall, low precision: aggressive classifier.
  - F_1-score is harmonic mean, punishing extreme imbalance between precision and recall.

Evaluation metrics like accuracy, precision, recall, and F1-score measure classifier performance. (7/8)

- Choosing the right metric is crucial, especially for imbalanced data and model comparison.
- When would you tolerate more false positives to catch almost every true case (prioritize recall)?
- When would you tolerate more misses to avoid false alarms (prioritize precision)?

Evaluation metrics like accuracy, precision, recall, and F1-score measure classifier performance. (8/8)

- Accuracy can be misleading for imbalanced classes (e.g., rare disease detection).
  - Example: 99% accuracy if classifier always predicts majority class.
  - For skewed data, prefer precision, recall, or F_β tailored to application risk.
  - E.g., spam detection: high recall, moderate precision.
  - Cross-validation strategies (e.g., stratified k-fold) provide robust estimates and control for class imbalance during evaluation.

Picking F_β: example scenarios

- Choose $F_{\beta=2}$ when recall matters more than precision (misses are costly).
  - Example: cancer screening triage; missing a true case is worse than a false alarm.
  - Example: safety incident detection; you want to catch nearly all real incidents.
- Choose $F_{\beta=1/2}$ when precision matters more than recall (false alarms are costly).
  - Example: automated legal holds; false positives are expensive to review.
  - Example: account freeze alerts; avoid disrupting legitimate users.

Part 2: Logistic Regression

Discriminative models directly model P(y|x), focusing on decision boundaries between classes. (1/4)

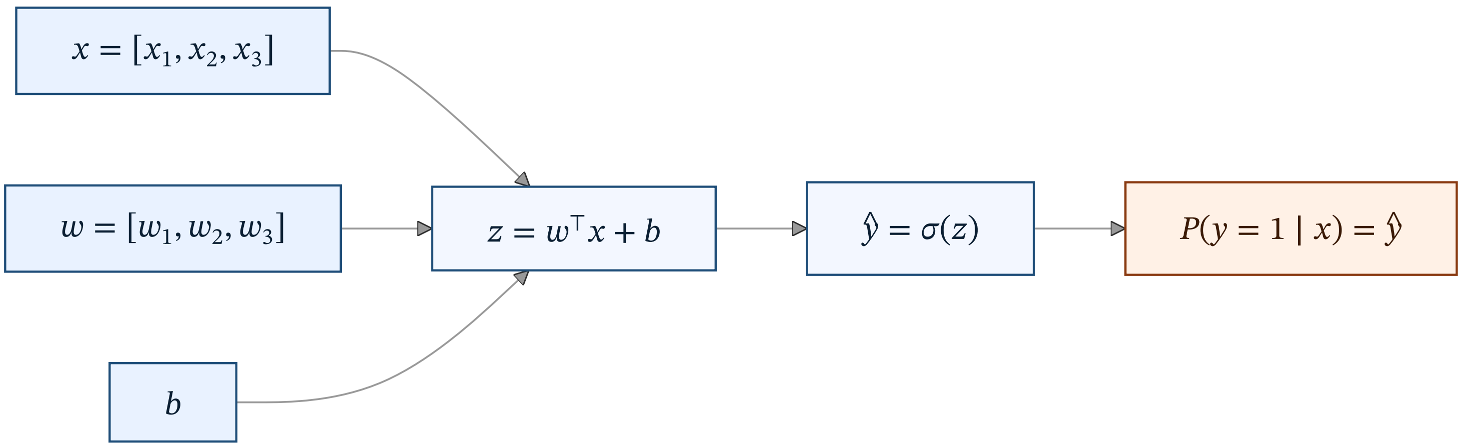
- Discriminative models directly estimate conditional probability $P(y|x)$, emphasizing decision boundaries.
  - The model focuses on learning the mapping from features x to labels y, rather than modeling $P(x)$ or $P(x, y)$.
  - Contrasts with generative models, which require explicit modeling of the joint distribution $P(x, y)$ or the marginal $P(x)$.
  - Inductive bias is centered on maximizing separation between classes in feature space.

Discriminative models directly model P(y|x), focusing on decision boundaries between classes. (2/4)

- Logistic regression leverages feature vectors x and weight parameters w to model $P(y=1|x)$ via the sigmoid activation.
  - The model computes:

$$P(y=1|x) = \sigma(w \cdot x + b) = \frac{1}{1 + e^{-(w \cdot x + b)}}$$

Logistic regression computes a weighted sum (logit) and applies a sigmoid.



Discriminative models directly model P(y|x), focusing on decision boundaries between classes. (3/4)

- Training involves optimizing weights w and bias b to minimize the cross-entropy loss:

$$\mathcal{L}(w, b) = -[y \log \hat{y} + (1 - y) \log(1 - \hat{y})]$$

- The decision boundary is the hyperplane $w \cdot x + b = 0$, learned directly from labeled data.

Logistic loss is the negative log-likelihood of a Bernoulli model. (1/1)

- Assume $y^{(i)} \in \{0, 1\}$ with Bernoulli likelihood:

$$p_\theta(y^{(i)} \mid x^{(i)}) = \hat{y}^{(i)y^{(i)}}(1 - \hat{y}^{(i)})^{1-y^{(i)}}, \quad \hat{y}^{(i)} = \sigma(w^\top x^{(i)} + b)$$

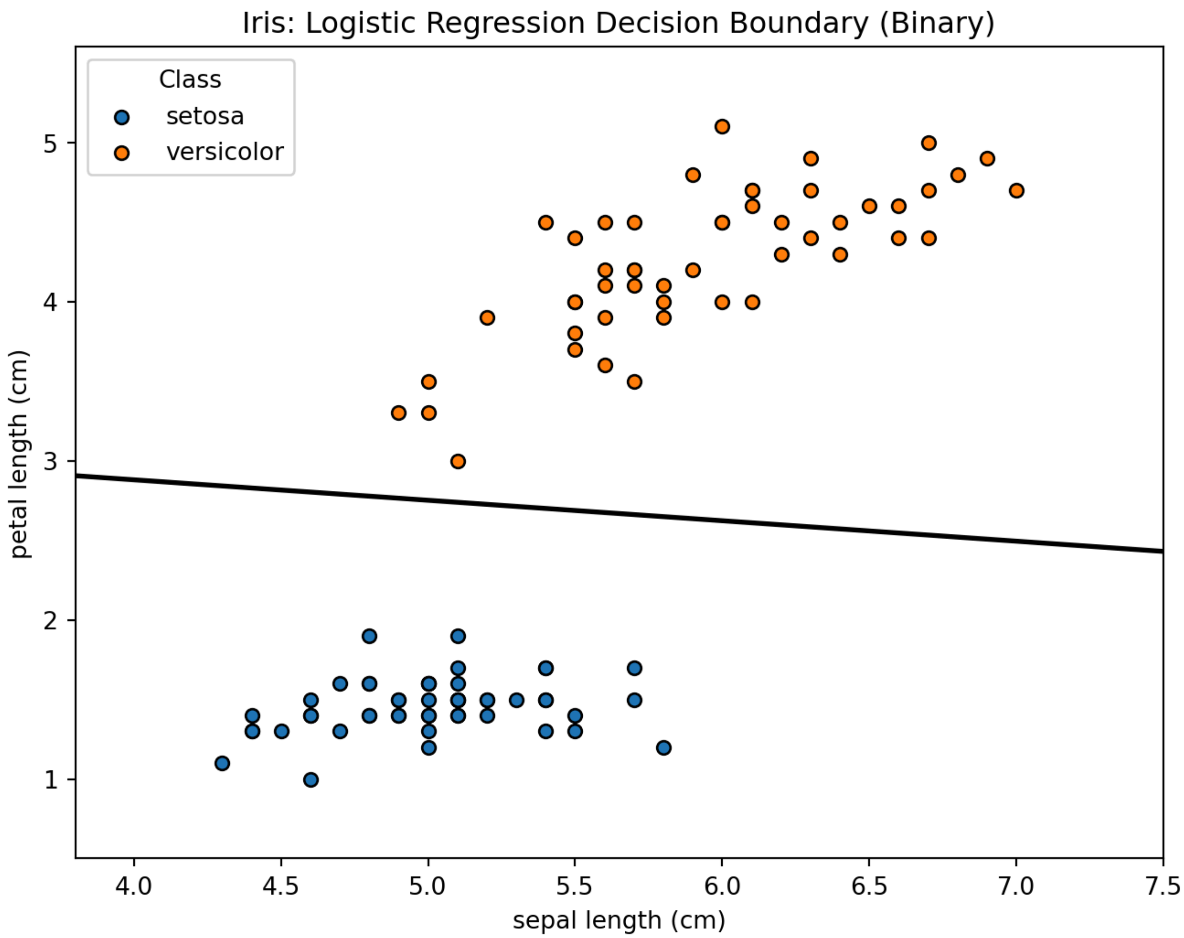
- MLE maximizes $\prod_i p_\theta(y^{(i)} \mid x^{(i)})$, equivalently minimizes negative log-likelihood:

$$-\sum_{i=1}^{N} \log p_\theta(y^{(i)} \mid x^{(i)}) = -\sum_{i=1}^{N} \left[y^{(i)} \log \hat{y}^{(i)} + (1 - y^{(i)}) \log(1 - \hat{y}^{(i)}) \right]$$

- This is exactly the binary cross-entropy (logistic) loss.

Iris dataset: binary classification

Classic Iris measurements (sepal/petal lengths) with logistic regression classifying setosa vs. versicolor using a 2D decision boundary.



Discriminative models directly model P(y|x), focusing on decision boundaries between classes. (4/4)

- Discriminative approaches enable robust text classification by allowing targeted feature engineering and direct optimization for accuracy.
  - Feature engineering can encode linguistic, lexical, or syntactic cues (e.g., word presence, n-grams, TF-IDF scores).
  - Empirical performance improves as features are tailored to the structure and nuances of text data.
  - Example: In sentiment classification, features such as polarity lexicon counts or phrase patterns can be incorporated to improve $P(y|x)$ estimation.

Binary logistic regression models the probability of a binary outcome using the sigmoid function. (1/7)

- Binary logistic regression models the probability of a binary outcome using the sigmoid function.
- For input $\mathbf{x} \in \mathbb{R}^d$, the model defines the probability of class $y \in \{0, 1\}$ as:

$$P(y = 1|\mathbf{x}; \mathbf{w}, b) = \sigma(\mathbf{w}^\top \mathbf{x} + b)$$

where $\sigma(z) = \frac{1}{1+e^{-z}}$ is the sigmoid activation.

Binary logistic regression models the probability of a binary outcome using the sigmoid function. (2/7)

- **Intuition:** The sigmoid maps real-valued scores to $[0, 1]$, enabling probabilistic interpretation for binary classification.

Applications:

- Text sentiment classification (positive/negative)
- Spam detection (spam/not spam)
- Medical diagnosis (disease/no disease)

Binary logistic regression models the probability of a binary outcome using the sigmoid function. (3/7)

- The model uses cross-entropy loss and optimizes parameters via (stochastic) gradient descent.
- The cross-entropy loss for a single data point is:

$$\mathcal{L}(\mathbf{w}, b) = -y \log \hat{y} - (1 - y) \log(1 - \hat{y})$$

where $\hat{y} = \sigma(\mathbf{w}^\top \mathbf{x} + b)$.

- For dataset $\{(\mathbf{x}^{(i)}, y^{(i)})\}_{i=1}^{N}$, the total loss:

$$\mathcal{J}(\mathbf{w}, b) = \frac{1}{N} \sum_{i=1}^{N} \mathcal{L}^{(i)}$$

Binary logistic regression models the probability of a binary outcome using the sigmoid function. (4/7)

Gradient Descent Algorithm:

- For each data point, compute the predicted probability $\hat{y}$ using the sigmoid function.
- Calculate gradients:
  - $\nabla_{\mathbf{w}} = (\hat{y} - y)\mathbf{x}$
  - $\nabla_b = (\hat{y} - y)$
- Update parameters:
  - $\mathbf{w} \leftarrow \mathbf{w} - \eta\nabla_{\mathbf{w}}$
  - $b \leftarrow b - \eta\nabla_b$

Binary logistic regression models the probability of a binary outcome using the sigmoid function. (5/7)

Binary logistic regression models the probability of a binary outcome using the sigmoid function. (6/7)

- Stochastic gradient descent (SGD) updates parameters using individual samples, improving convergence on large datasets.
- This enables effective classification and sets the stage for regularization to prevent overfitting.
- Logistic regression provides probabilistic outputs, interpretable coefficients, and a convex loss surface, facilitating robust training.
- Overfitting can occur, especially with high-dimensional data; regularization (e.g., L1, L2 penalties) mitigates this by constraining parameter magnitudes.

Binary logistic regression models the probability of a binary outcome using the sigmoid function. (7/7)

Next:

- We will examine regularization strategies and their effect on generalization in logistic regression.

Regularization penalties prevent overfitting by constraining parameter magnitudes. (1/3)

- Regularization adds a penalty term to the loss function to discourage large parameter values.
  - L_p norm: $\|\mathbf{w}\|_p = \left(\sum_{j=1}^{d} |w_j|^p\right)^{1/p}$
  - L_1 regularization (Lasso): $\|\mathbf{w}\|_1 = \sum_{j=1}^{d} |w_j|$
  - L_2 regularization (Ridge): $\|\mathbf{w}\|_2^2 = \sum_{j=1}^{d} w_j^2$
- Regularized loss:

$$\mathcal{J}_{\text{reg}}(\mathbf{w}, b) = \frac{1}{N} \sum_{i=1}^{N} \mathcal{L}^{(i)} + \lambda \|\mathbf{w}\|_p$$

where λ controls the regularization strength.

Regularization penalties prevent overfitting by constraining parameter magnitudes. (2/3)

- **L2 regularization** derives from a Gaussian prior on weights:
  - Prior: $p(\mathbf{w}) \propto \exp\left(-\frac{\lambda}{2}\|\mathbf{w}\|_2^2\right)$
  - MAP estimation adds the penalty $\lambda\|\mathbf{w}\|_2^2$ to the loss.
- **L1 regularization** derives from a Laplace (double exponential) prior:
  - Prior: $p(\mathbf{w}) \propto \exp\left(-\lambda\|\mathbf{w}\|_1\right)$
  - MAP estimation adds the penalty $\lambda\|\mathbf{w}\|_1$ to the loss.

Regularization penalties prevent overfitting by constraining parameter magnitudes. (3/3)

- L1 regularization promotes sparsity by setting many weights to zero, enabling feature selection.
- L2 regularization shrinks weights uniformly, improving generalization without feature selection.
- Practical guidance:
  - Use L2 (Ridge) for dense feature spaces or when all features may be informative.
  - Use L1 (Lasso) when feature selection is desired or the feature space is sparse.
  - Elastic Net combines L1 and L2 for balanced regularization.

Multiclass logistic regression can be done via one-vs-rest or softmax approaches. (1/3)

- Multiclass logistic regression can be performed using either one-vs-rest or softmax approaches.
  - In the one-vs-rest (OvR) strategy, K binary classifiers are trained, one per class, each distinguishing one class from all others.
  - For class k, the classifier computes $P(y = k \mid \mathbf{x}) = \sigma(\mathbf{w}_k^\top \mathbf{x} + b_k)$
  - The predicted class is $\arg\max_k P(y = k \mid \mathbf{x})$.
  - The softmax approach generalizes logistic regression to multiple classes by modeling all classes jointly.

Multiclass logistic regression can be done via one-vs-rest or softmax approaches. (2/3)

- For K classes, the probability of class k is:

$$P(y = k \mid \mathbf{x}) = \frac{\exp(\mathbf{w}_k^\top \mathbf{x} + b_k)}{\sum_{j=1}^{K} \exp(\mathbf{w}_j^\top \mathbf{x} + b_j)}$$

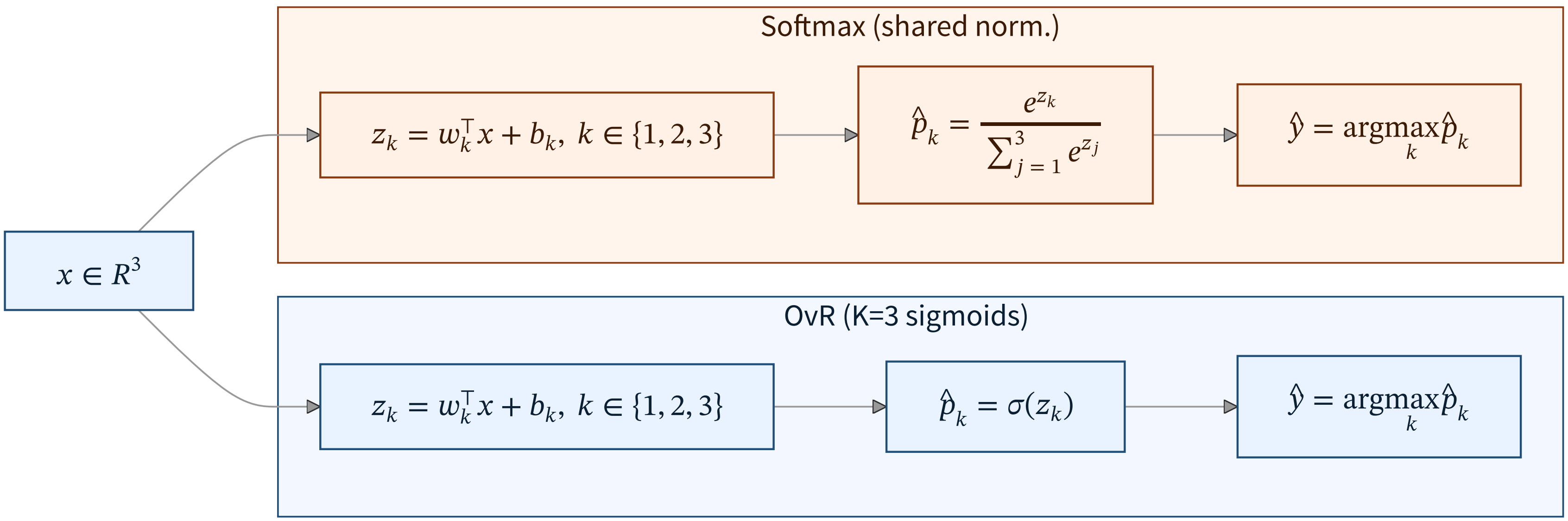
- The predicted class is again $\arg\max_k P(y = k \mid \mathbf{x})$.
  - Both approaches use the cross-entropy loss, but the softmax formulation yields a single, vector-valued gradient, while OvR involves K separate binary losses.

Multiclass logistic regression can be done via one-vs-rest or softmax approaches. (3/3)

Applications:

- Text classification with more than two categories (e.g., topic or sentiment classification).
- Part-of-speech tagging, where each word must be assigned to one of many possible tags.

Multiclass logistic regression: OvR vs. softmax (diagram)



Takeaways:

- OvR is simpler to train with binary solvers and allows per-class thresholds.
- Softmax provides a single, normalized probability distribution across classes.

Part 3: Statistical and Experimental Considerations

Statistical significance testing is essential for validating NLP experiment results. (1/8)

- Example: Trained logistic regression on a toy spam/ham dataset.
- We evaluate predictions with a confusion matrix before running significance tests.

Statistical significance testing is essential for validating NLP experiment results. (2/8)

- Statistical hypothesis testing quantifies whether observed performance differences are likely due to chance.
  - Null hypothesis H_0: No difference between systems' true performance.
  - p-value: Probability of observing results at least as extreme as those measured, assuming H_0 is true.

Statistical significance testing is essential for validating NLP experiment results. (3/8)

- In NLP, model evaluation metrics (e.g., accuracy, F1) are subject to sampling noise.
  - Random train/test splits and annotation errors introduce variance.
  - Without significance testing, small metric improvements may be spurious.
- Example:
  - Comparing two classifiers with 80.2% vs. 80.7% accuracy on a test set of size N.
  - Is the 0.5% difference meaningful, or within random variation?

Statistical significance testing is essential for validating NLP experiment results. (4/8)

Methods like bootstrap confidence intervals and tests across datasets assess result reliability.

- The bootstrap estimates confidence intervals by repeatedly resampling the test set:

$$\text{For } b = 1, \ldots, B: \quad \text{Sample with replacement to create set } D_b$$

$$\text{Compute metric: } \theta^{(b)} = \text{Metric}(D_b)$$

$$\text{Form empirical distribution: } \{\theta^{(1)}, \ldots, \theta^{(B)}\}$$

Statistical significance testing is essential for validating NLP experiment results. (5/8)

Statistical significance testing is essential for validating NLP experiment results. (6/8)

- Significance testing across datasets (e.g., paired t-test, approximate randomization) accounts for correlation and variance:
  - Paired t-test: Compare metric differences per example across systems.
  - Randomization: Shuffle system outputs to simulate null hypothesis.
- Application:
  - Dror et al. (2017) recommend testing across multiple datasets for robustness.

Statistical significance testing is essential for validating NLP experiment results. (7/8)

Proper significance reporting ensures replicability and trust in classification experiments.

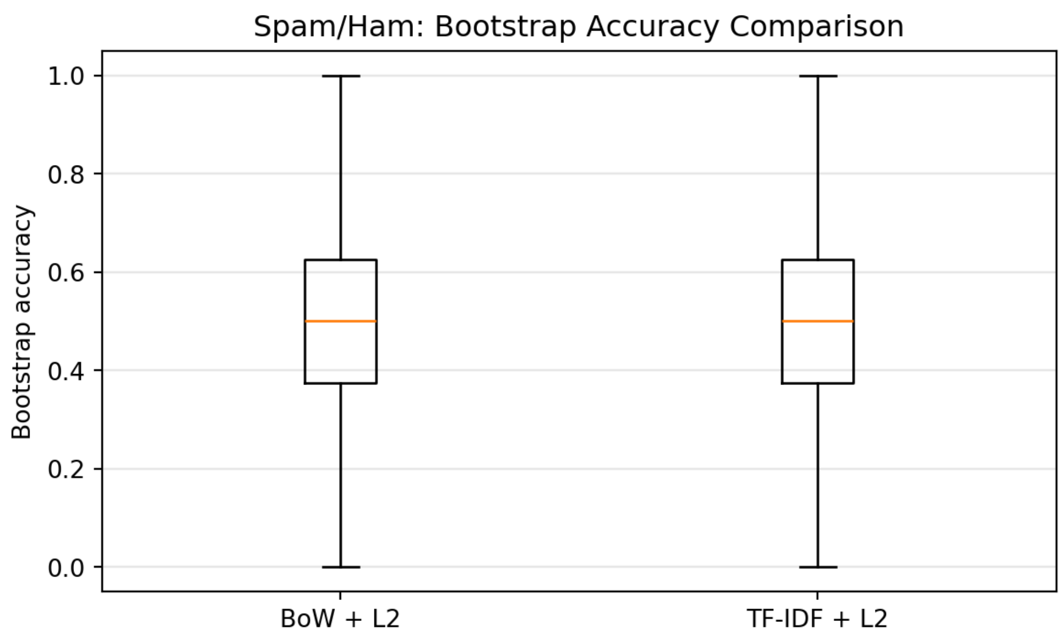
- Reporting standards include:
  - Declaring test set size, number of runs, and test statistic used.
  - Reporting confidence intervals, not just point estimates.

Statistical significance testing is essential for validating NLP experiment results. (8/8)

- Replicability crisis in NLP highlights the necessity of statistical rigor.
- Example reporting statement:
  - "System A outperforms System B on F1 ($p = 0.03$, 95% CI: [0.02, 0.08]) across 10 datasets."

Bootstrap comparison: spam/ham text models

- Model A: Bag-of-words counts + L2 logistic regression.
- Model B: TF-IDF unigrams + L2 logistic regression.



Part 4: Case Study: 20 Newsgroups Classification

20 Newsgroups: classification task

- Predict the discussion group label from the post text.
- Usenet posts from 20 topical forums (sports, politics, tech, religion).
- 20 categories, balanced enough that accuracy is meaningful.
- We strip headers/footers/quotes to focus on content.

Dataset overview

- Train/test splits come from scikit-learn's `fetch_20newsgroups`.
- Each example is a short, noisy, user-generated post.

OUTPUT

```
Train size: 11314  Test size: 7532
Classes: 20
```

Example posts (truncated)

- Look for topical keywords that hint at the group label.

OUTPUT

```
[rec.autos] I was wondering if anyone out there could enlighten me on this car I saw the other
day. It was a 2-door sports car, looked to be from the late 60s/ early 70s. It was called a...

[comp.sys.mac.hardware] --

[comp.graphics] Hello, I am looking to add voice input capability to a user interface I am
developing on an HP730 (UNIX) workstation. I would greatly appreciate information anyone would
care to...
```

Bigram example: phrase cues

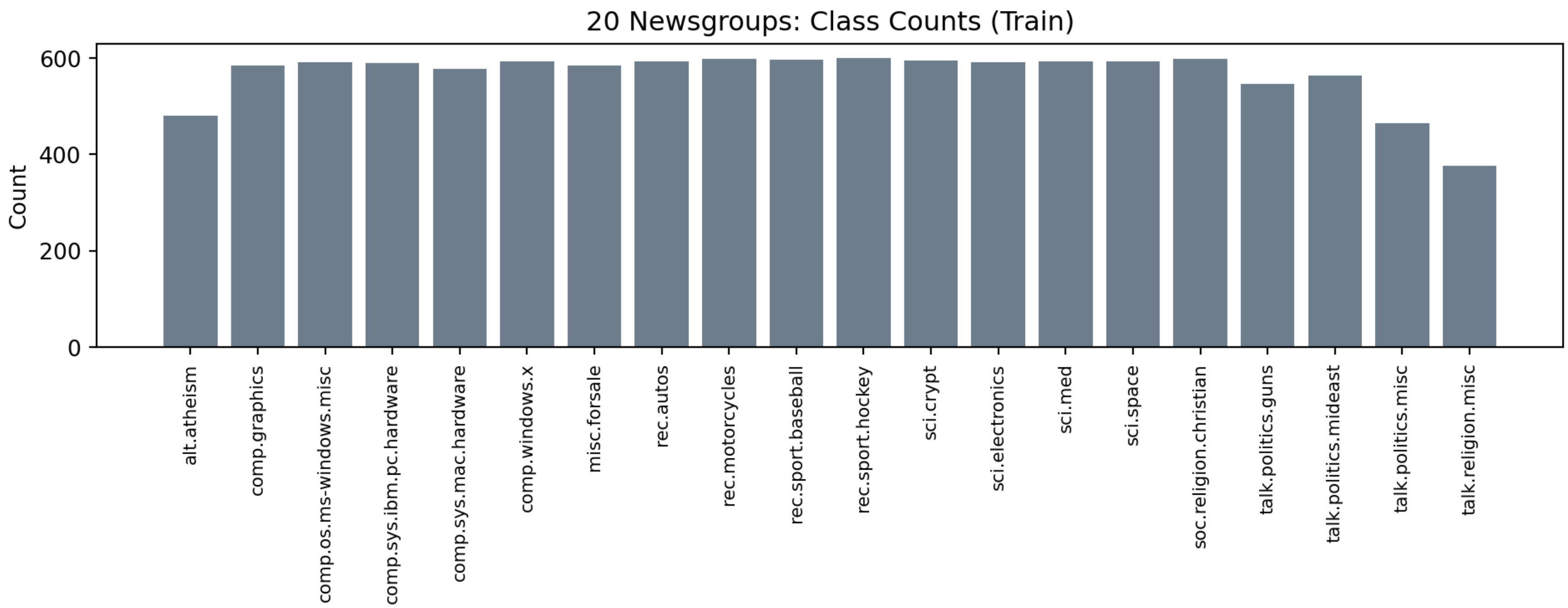
- Bigrams capture short phrases (e.g., “space shuttle”, “power supply”).

OUTPUT

```
Example bigrams: ['60s early' 'info funky' 'know tellme' 'late 60s' 'looked late'
 'looking car' 'model engine' 'production car' 'really small' 'saw day']
```

Class distribution (train split)

- Classes are roughly balanced, but not perfectly uniform.



Model A: TF-IDF unigrams + L2 logistic regression

- TF-IDF reduces weight on common terms.
- L2 regularization discourages overly large weights.
- Strong baseline with relatively compact feature space.

Model B: TF-IDF unigrams+bigrams + L1 logistic regression

- Bigrams add short-phrase cues.
- L1 encourages sparse, feature-selective weights.
- More features, higher risk of overfitting on small topics.

Accuracy + micro/macro precision/recall/F1

- Micro averages track overall correctness; macro highlights per-class balance.
- **Micro:** pool all predictions, then compute global $P/R/F_1$ from total TP/FP/FN.
- **Macro:** compute $P/R/F_1$ per class, then average (each class equal weight).

OUTPUT

```
Model A: acc=0.648
  micro: P=0.648 R=0.648 F1=0.648
  macro: P=0.650 R=0.635 F1=0.636
Model B: acc=0.557
  micro: P=0.557 R=0.557 F1=0.557
  macro: P=0.619 R=0.546 F1=0.567
```

F_β emphasizes recall when $\beta > 1$

- Example: F_2 weights recall higher than precision.
- Useful when missing a topic is costlier than a false alarm.

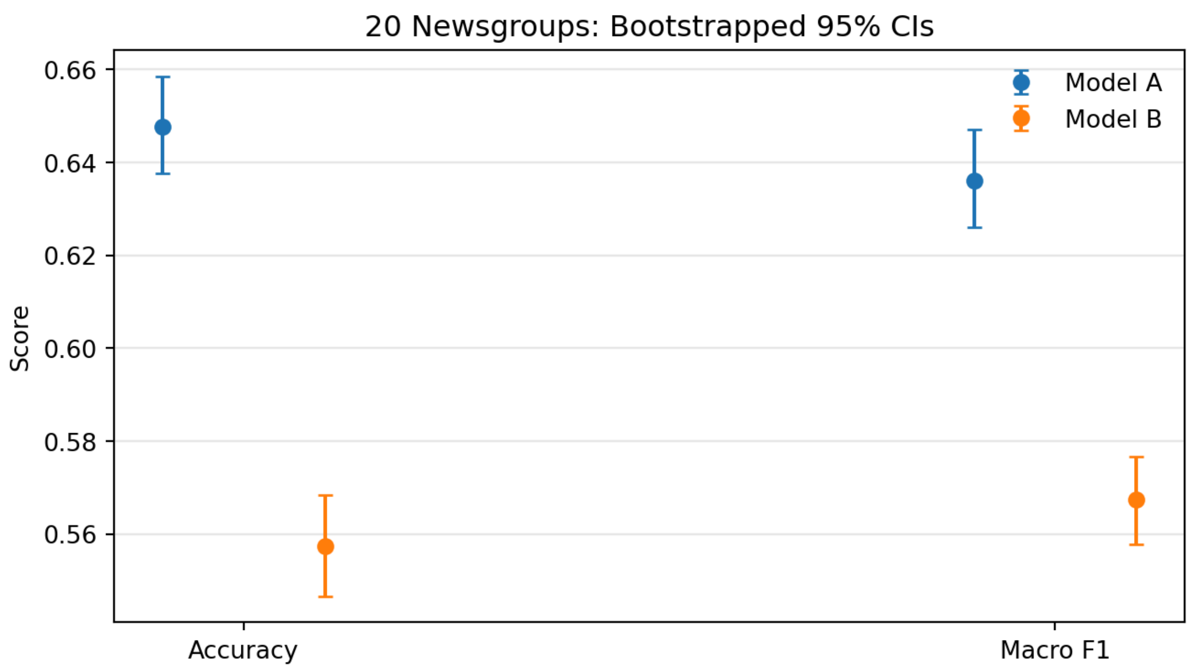
OUTPUT

```
Model A F2: 0.634
Model B F2: 0.550
```

Confusion matrix (best macro F1)

Bootstrapped confidence intervals

- 95% CIs for accuracy and macro F1.
- Overlapping intervals would suggest weak evidence of a difference.



Model comparison takeaways

- Model A is a strong, simple baseline with fewer features.
- Model B adds phrase cues but can trade speed for sparsity.
- Macro metrics and the confusion matrix show where each model struggles.