An Empirical Study of Skip-gram Features and Regularization for Learning on Sentiment Analysis

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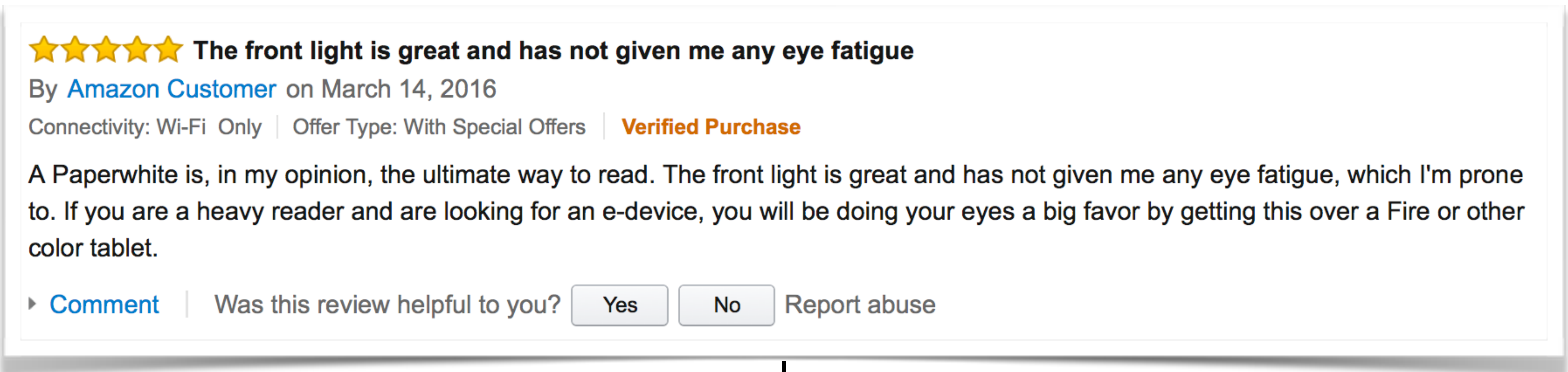
Sentiment Analysis

An Amazon Product Review



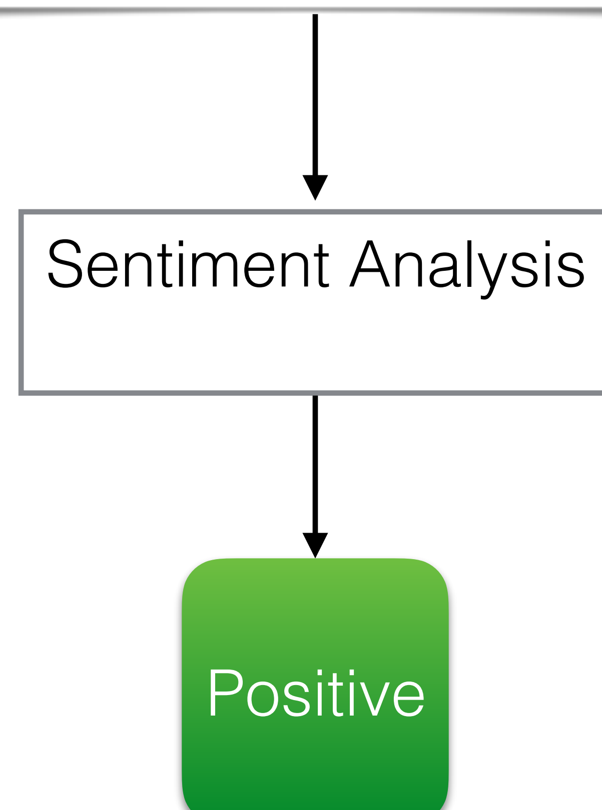
The front light is great and has not given me any eye fatigue

By Amazon Customer on March 14, 2016

Connectivity: Wi-Fi Only | Offer Type: With Special Offers | **Verified Purchase**

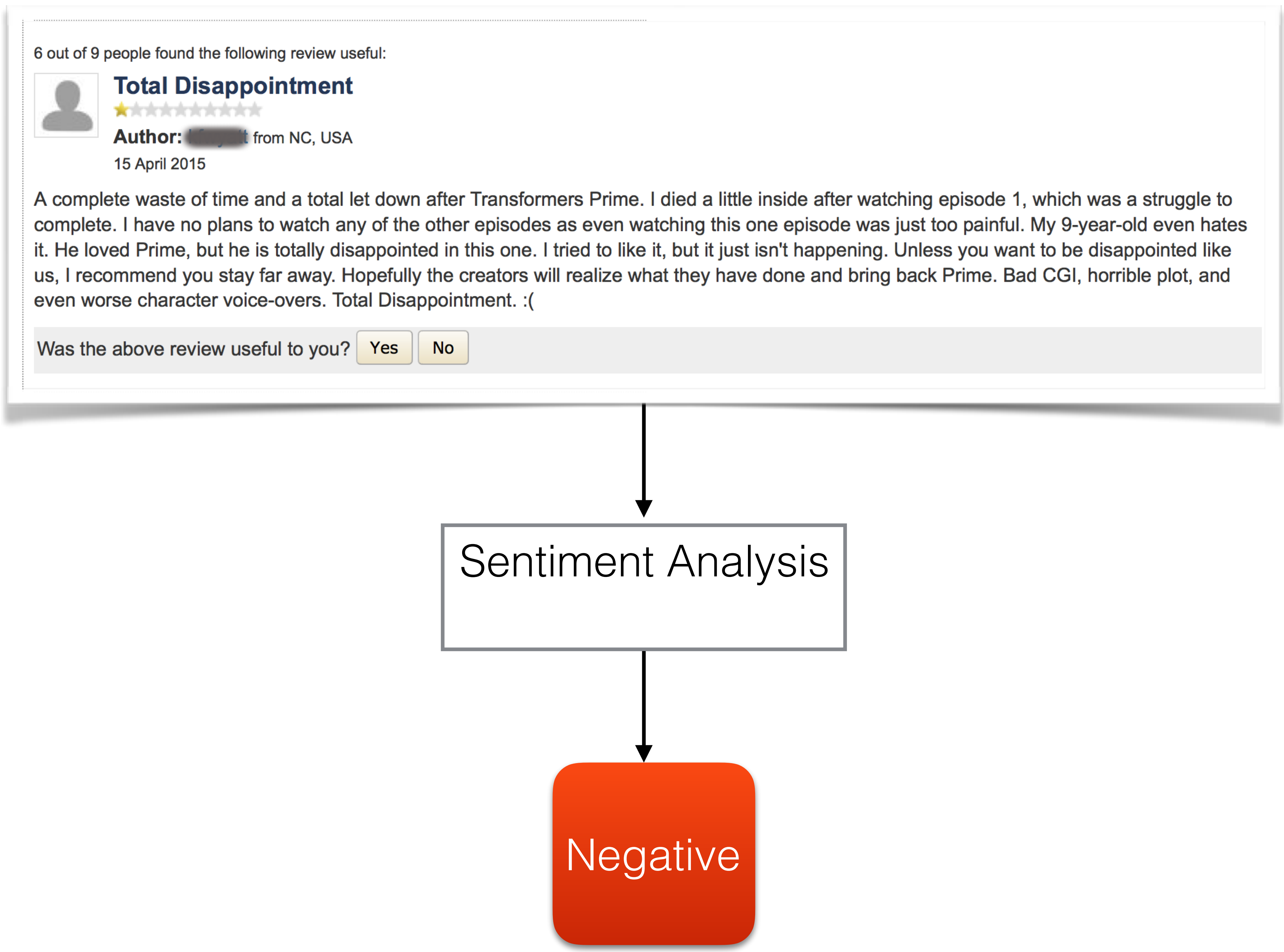
A Paperwhite is, in my opinion, the ultimate way to read. The front light is great and has not given me any eye fatigue, which I'm prone to. If you are a heavy reader and are looking for an e-device, you will be doing your eyes a big favor by getting this over a Fire or other color tablet.

Comment | Was this review helpful to you? Yes No Report abuse



Sentiment Analysis

An IMDB Movie Review



6 out of 9 people found the following review useful:

Total Disappointment

Author: [redacted] from NC, USA

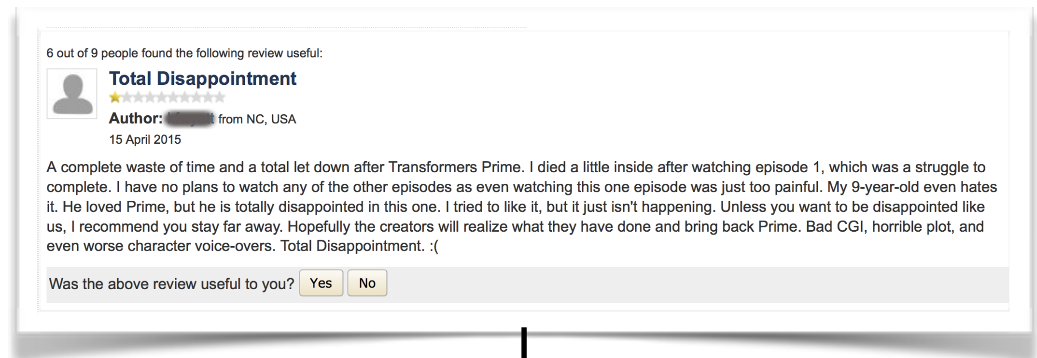
15 April 2015

A complete waste of time and a total let down after Transformers Prime. I died a little inside after watching episode 1, which was a struggle to complete. I have no plans to watch any of the other episodes as even watching this one episode was just too painful. My 9-year-old even hates it. He loved Prime, but he is totally disappointed in this one. I tried to like it, but it just isn't happening. Unless you want to be disappointed like us, I recommend you stay far away. Hopefully the creators will realize what they have done and bring back Prime. Bad CGI, horrible plot, and even worse character voice-overs. Total Disappointment. :(

Was the above review useful to you? Yes No

Sentiment Analysis with Binary Text Classification Pipeline

Review Document → Feature Vector → Classifier → Prediction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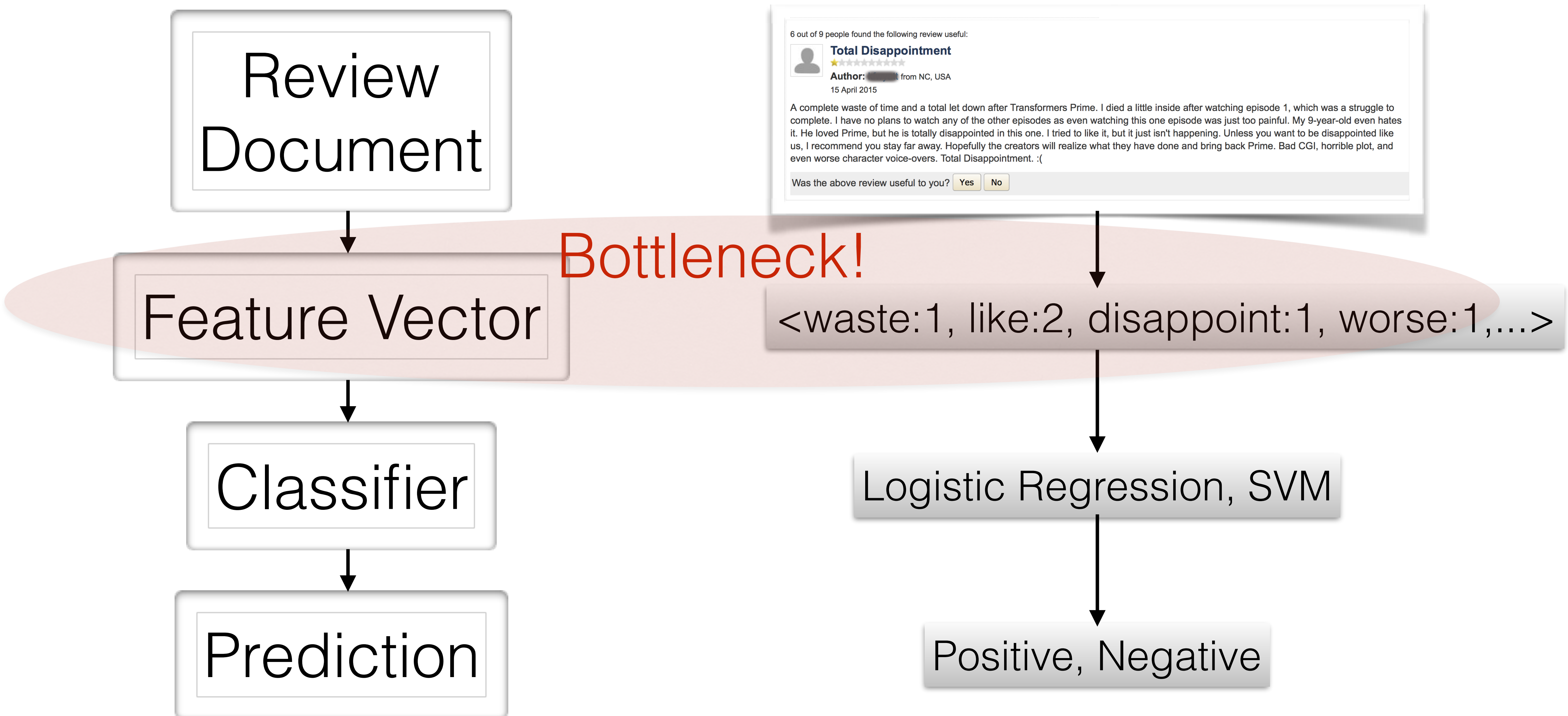
<waste:1, like:2, disappoint:1, worse:1,...>

Logistic Regression, SVM

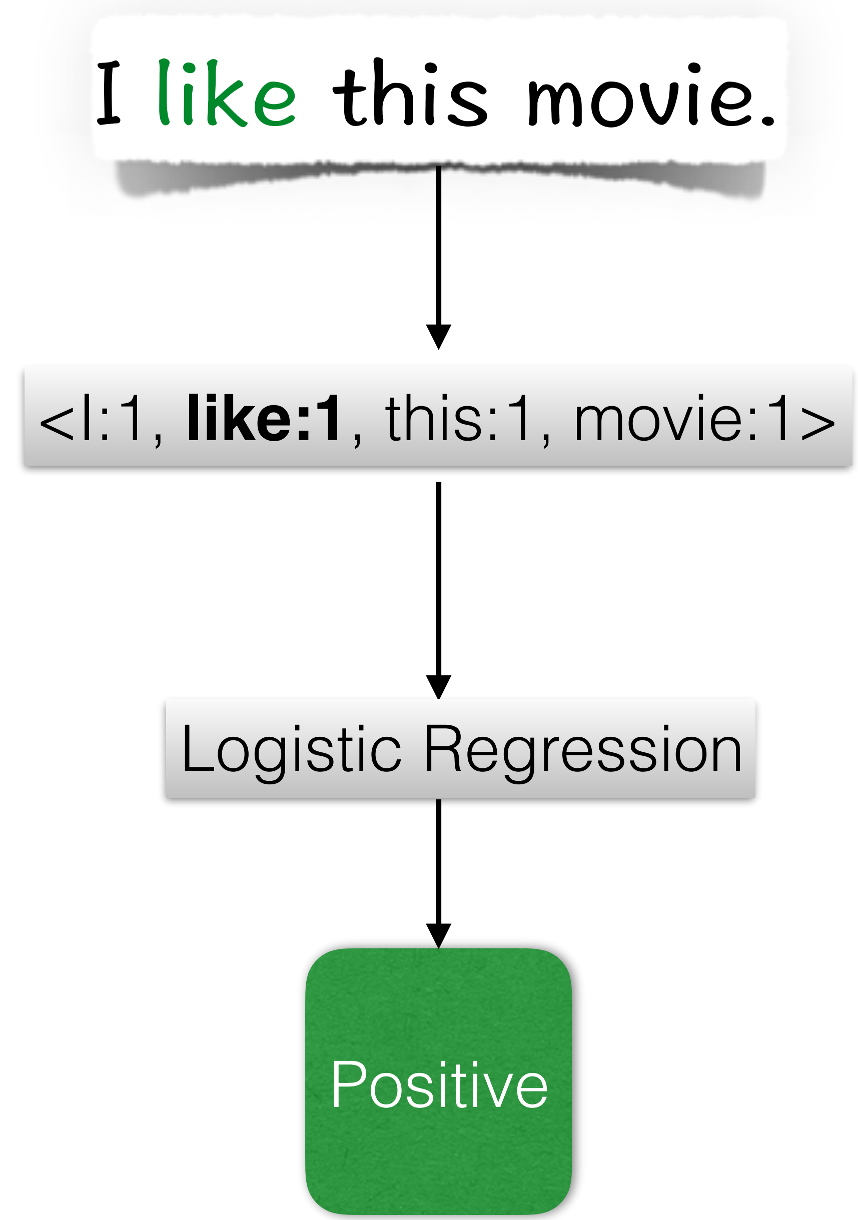
Positive, Negative

Sentiment Analysis with Binary Text Classification Pipeline



Text Representation Issues in Sentiment Analysis

- Unigram (bag of words)
  capture sentiment indicator terms



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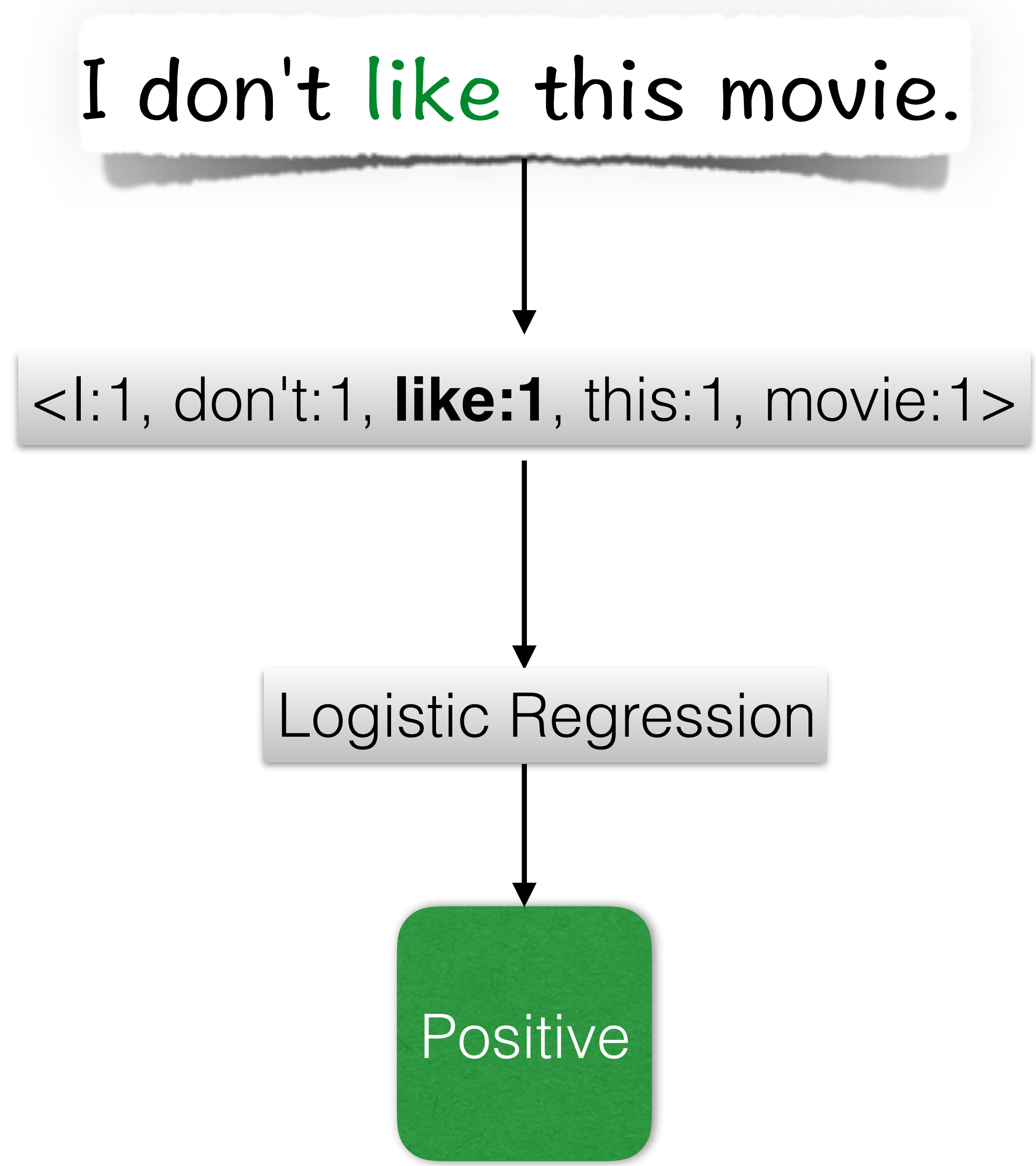

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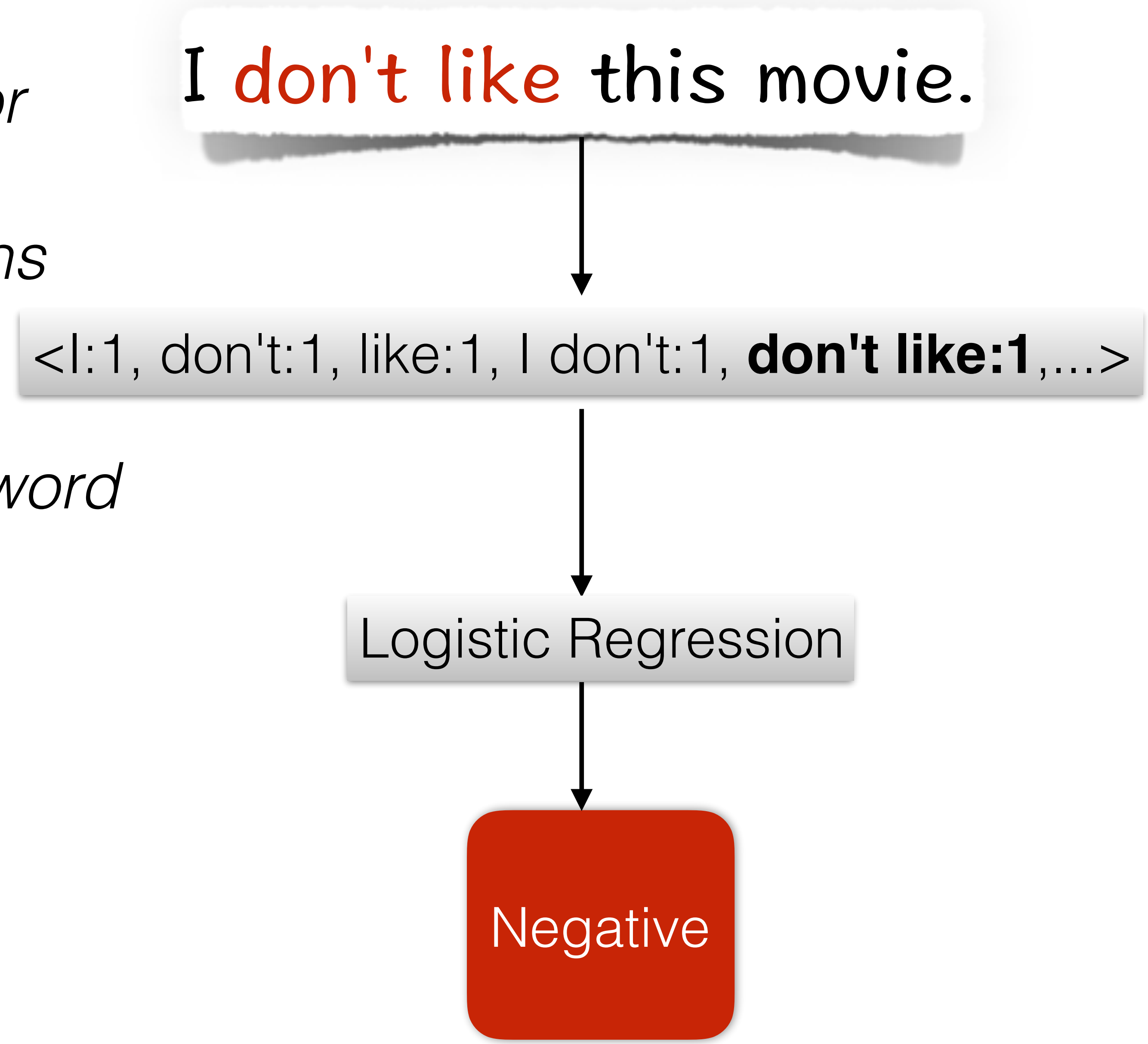
- Add Bi-grams
  capture negation-polarity word pairs



Text Representation Issues in Sentiment Analysis

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- Add Bi-grams
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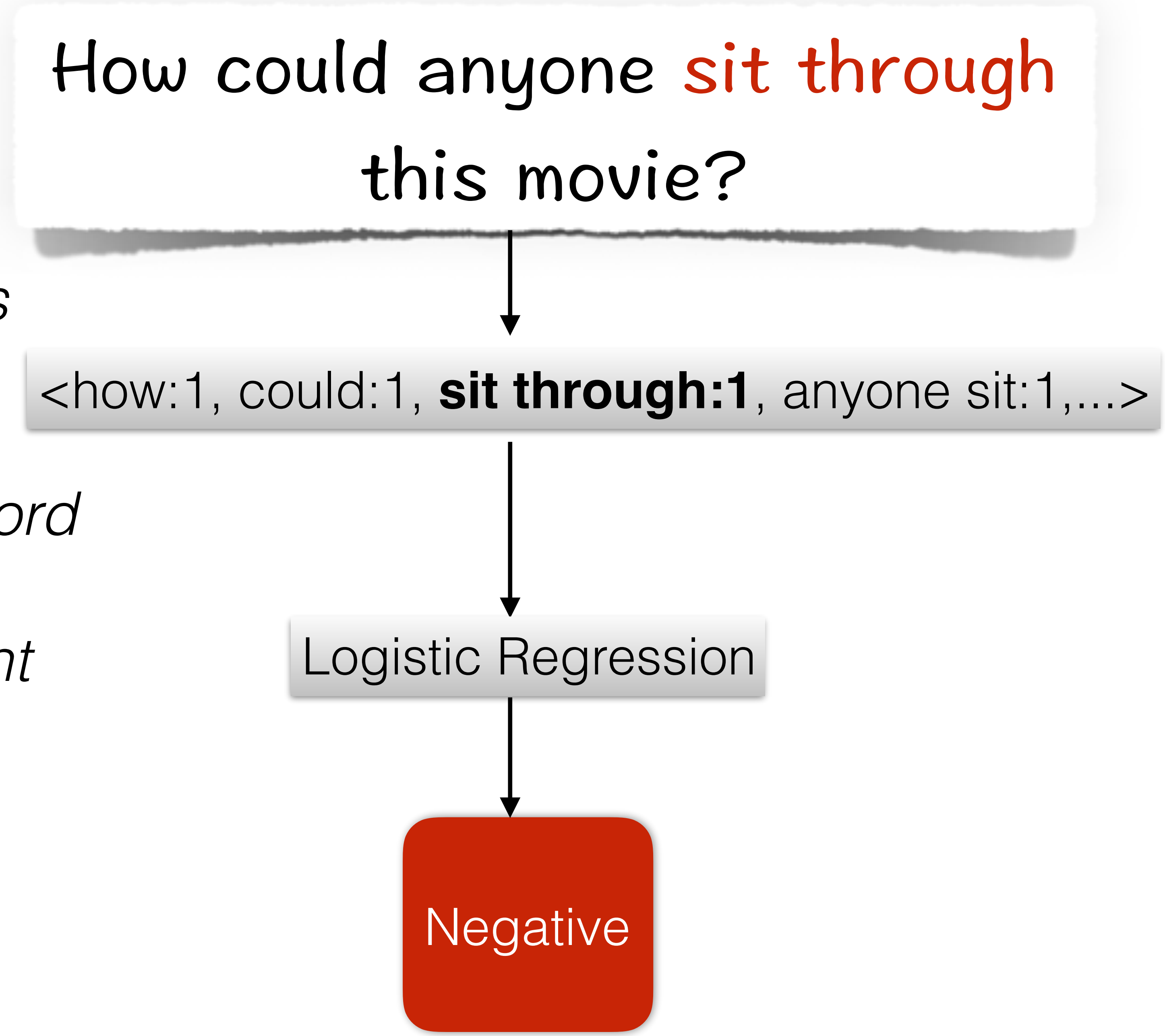
  capture two-words sentiment phrases



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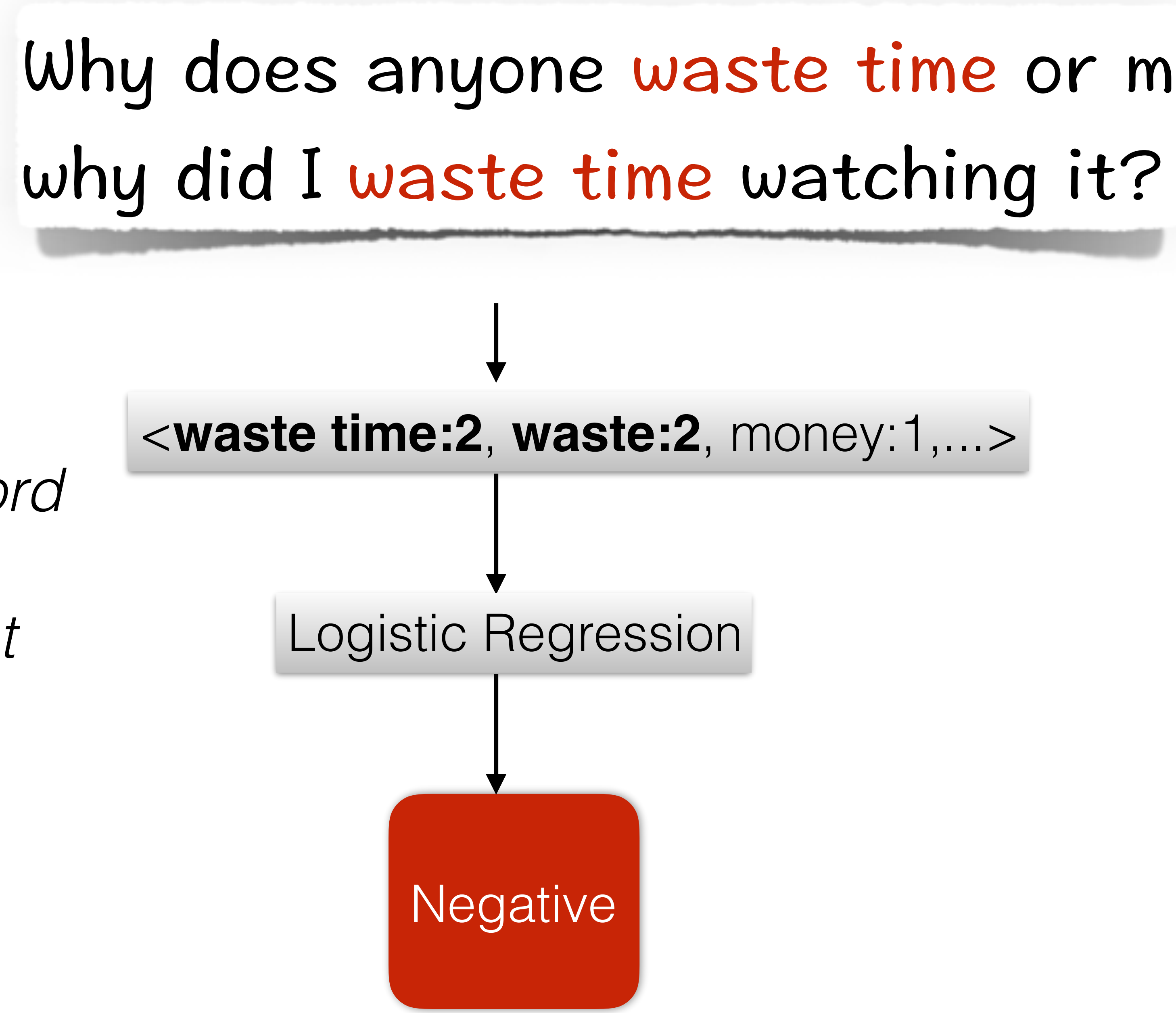


Text Representation Issues in Sentiment Analysis

- Unigram (bag of words)
  capture sentiment indicator terms
  could not capture negations

- Add Bi-grams
  capture negation-polarity word pairs
  capture two-words sentiment phrases

- Add tri-grams,quad-grams...
  capture sentiment phrases with many words

Don't waste your time on this movie.

So annoying and such a waste of my time.

A complete waste of time.

I wasted a lot of time on it.

I wasted too much time on it.

Difficulty with High Order n-grams

- Many variations

  "waste your time"

  "waste of my time"

  "waste of time"

  "wasted a lot of time"

  "wasted too much time"

  → increase the dimensionality

- rare cases

  "waste of time": 676 times in IMDB

  "waste more time": 6 times

  "waste your time": 4 times

  → insufficient data for parameter estimation

Skip-grams

- n-gram templates matched loosely
- Looseness parameterized by ***slop***, the number of additional words
- n-gram = skip-gram with ***slop*** 0

Skip-gram Examples

skipgram and count		matched ngrams and count			
skip movie (slop 2)	42	skip this movie	28	skip this pointless movie	1
		skip the movie	8	skipping all the movies (of this sort)	1
		skip watching this movie	1		
it fail (slop 1)	358	it fails	279	it completely fails	5
		it even fails	5	it simply fails	3
whole thing (slop 1)	729	whole thing	682	whole horrific thing	1
		whole damn thing	5		
waste time (slop 1)	1562	waste time	109	waste of time	676
		waste your time	4	waste more time	6
only problem (slop 1)	1481	only problem	1378	only tiny problem	4
		only minor problem	11		
never leak (slop 2)	1053	never leak	545	never a urine leak (problem)	1
		never have leak	86	never have any leak	77
no smell (slop 1)	445	no smell	340	no medicine-like smell	1
		no bad smell	13	no annoying smell	5
it easy to clean and (slop 2)	314	it is easy to wipe clean and	3	it is easy to keep clean and	3
		it is so easy to clean and	16		
I have to return (slop 2)	216	I have to return	151	I finally have to return	1
		I have never had to return	1	I do not have to return	4
good service (slop 2)	209	good service	131	good price and service	1
		good and fast service	2		

Advantages of Skip-grams

- Group infrequent n-grams into a frequent skip-gram
- Allow n-grams to borrow strength from each other
- Easier learning
- Better generalization

Difficulties with Skip-grams

- Huge number
- Many are non-informative or noisy

  skip-gram "I recommend" with *slop* 2 can match both "I highly recommend" and "I do not recommend"

Existing Use of Skip-grams in Sentiment Analysis

- Ask human assessors to pick informative skip-grams
  - ✗ limited by available domain knowledge
  - ✗ expensive
- Build dense word vectors on top of skip-grams
  - ✗ information loss
  - ✗ less interpretable

Goal of this Study

- Test whether skip-grams are helpful when used directly as features in sentiment analysis
- Test different automatic regularization/feature selection strategies
- Compare against n-grams and word vectors

Skip-gram Extraction

- Consider skip-grams with *n*<=5 and *slop*<=2 (5-grams with 2 additional words in between)

- Discard skip-grams with very low frequencies (<=5)

max *n*	max *slop*	# skip-grams on IMDB
1	0	2x10^4
2	0	1x10^5
3	0	2x10^5
5	0	4x10^5
2	1	3x10^5
3	1	9x10^5
5	1	1x10^6
2	2	6x10^5
3	2	2x10^6
5	2	3x10^6

L1 vs L2 regularization

- Skip-gram features: huge number, correlated
- L1: $\min_w \text{ loss} + \lambda ||w||_1$
  - ✓ shrink weights
  - ✓ select a subset of features → compact model
  - ✗ select one out of several correlated features
- L2: $\min_w \text{ loss} + \lambda ||w||_2^2$
  - ✓ shrink weights
  - ✗ use all features → robust model
  - ✓ spread weight among correlated features

L1+L2 regularization

- L1+L2: $\min_w \text{ loss} + \lambda\alpha||w||_1 + \lambda(1-\alpha)||w||_2^2$
  - ✓ shrink weights
  - ✓ select a subset of features → compact model
  - ✓ spread weight among correlated features → robust model

Learning and Regularization

- L2-regularized linear SVM

$$\min_w \sum_{i=1}^{N} (\max(0, 1 - y_i w^T x_i))^2 + \lambda \frac{1}{2} ||w||_2^2$$

- L1-regularized linear SVM

$$\min_w \sum_{i=1}^{N} (\max(0, 1 - y_i w^T x_i))^2 + \lambda ||w||_1$$

- L2-regularized Logistic Regression

$$\min_w -\frac{1}{N} \sum_{i=1}^{N} y_i w^T x_i + \log(1 + e^{w^T x_i}) + \lambda \frac{1}{2} ||w||_2^2$$

- L1-regularized Logistic Regression

$$\min_w -\frac{1}{N} \sum_{i=1}^{N} y_i w^T x_i + \log(1 + e^{w^T x_i}) + \lambda ||w||_1$$

- L1+L2-regularized Logistic Regression

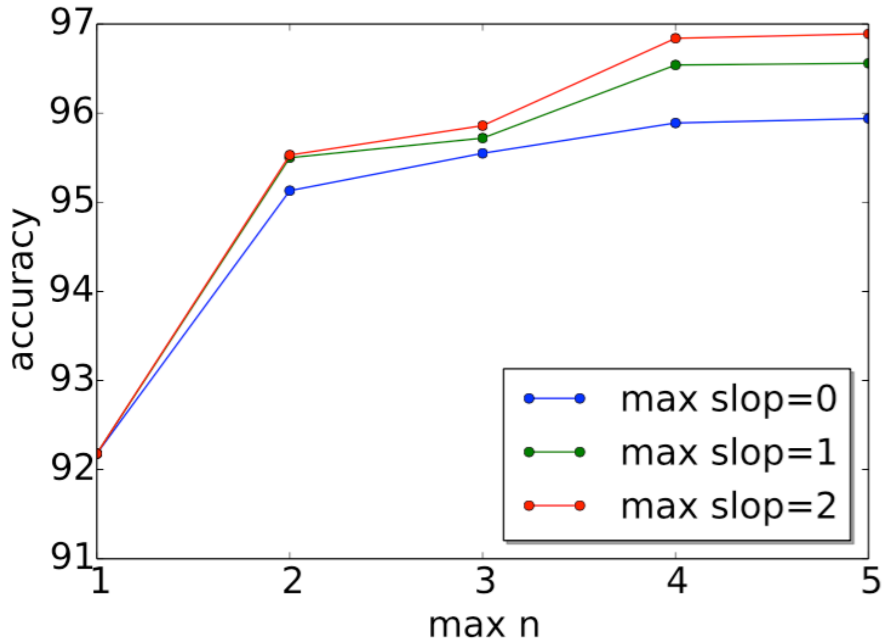
$$\min_w -\frac{1}{N} \sum_{i=1}^{N} y_i w^T x_i + \log(1 + e^{w^T x_i}) + \lambda \alpha ||w||_1 + \lambda (1 - \alpha) \frac{1}{2} ||w||_2^2$$

Datasets

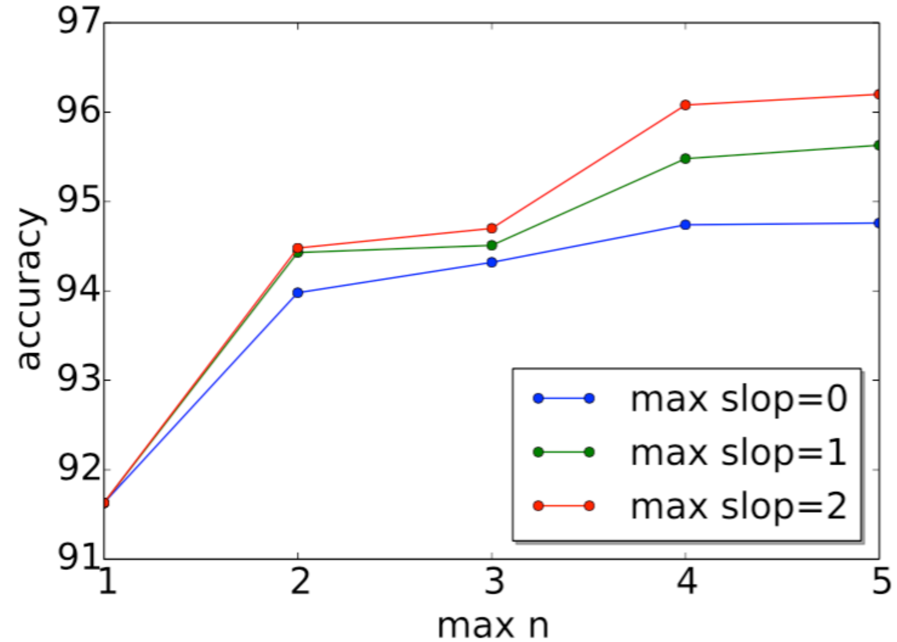
Binary classification with neutral reviews ignored

dataset	positive	negative
IMDB	25,000 reviews with ratings 7-10	25,000 reviews with ratings 1-4
Amazon Baby Product	136,461 reviews with ratings 4-5	32,950 reviews with ratings 1-2
Amazon Phone Product	47,970 reviews with ratings 4-5	22,241 reviews with ratings 1-2

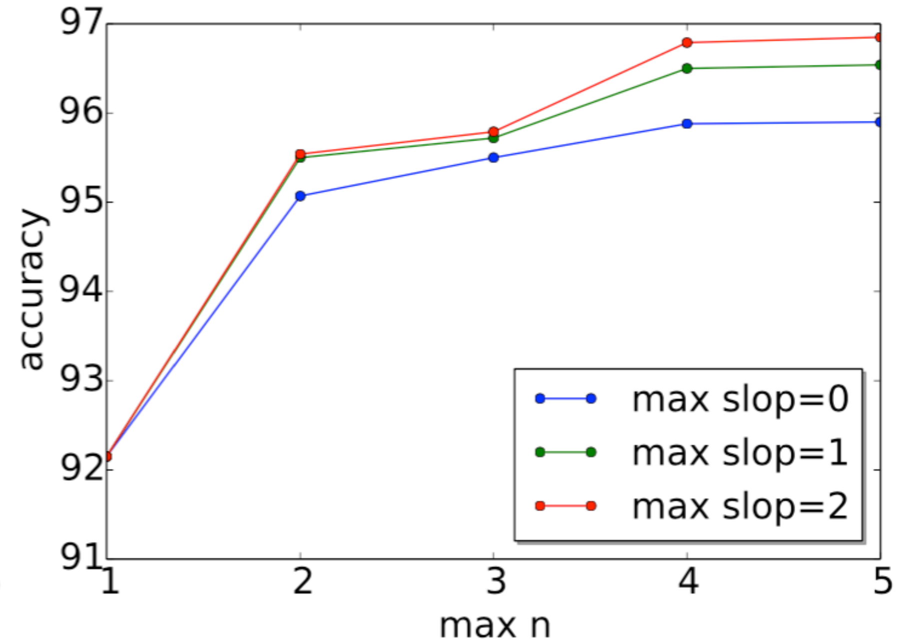
Classification Accuracy with Skip-gram Features



L2 LR



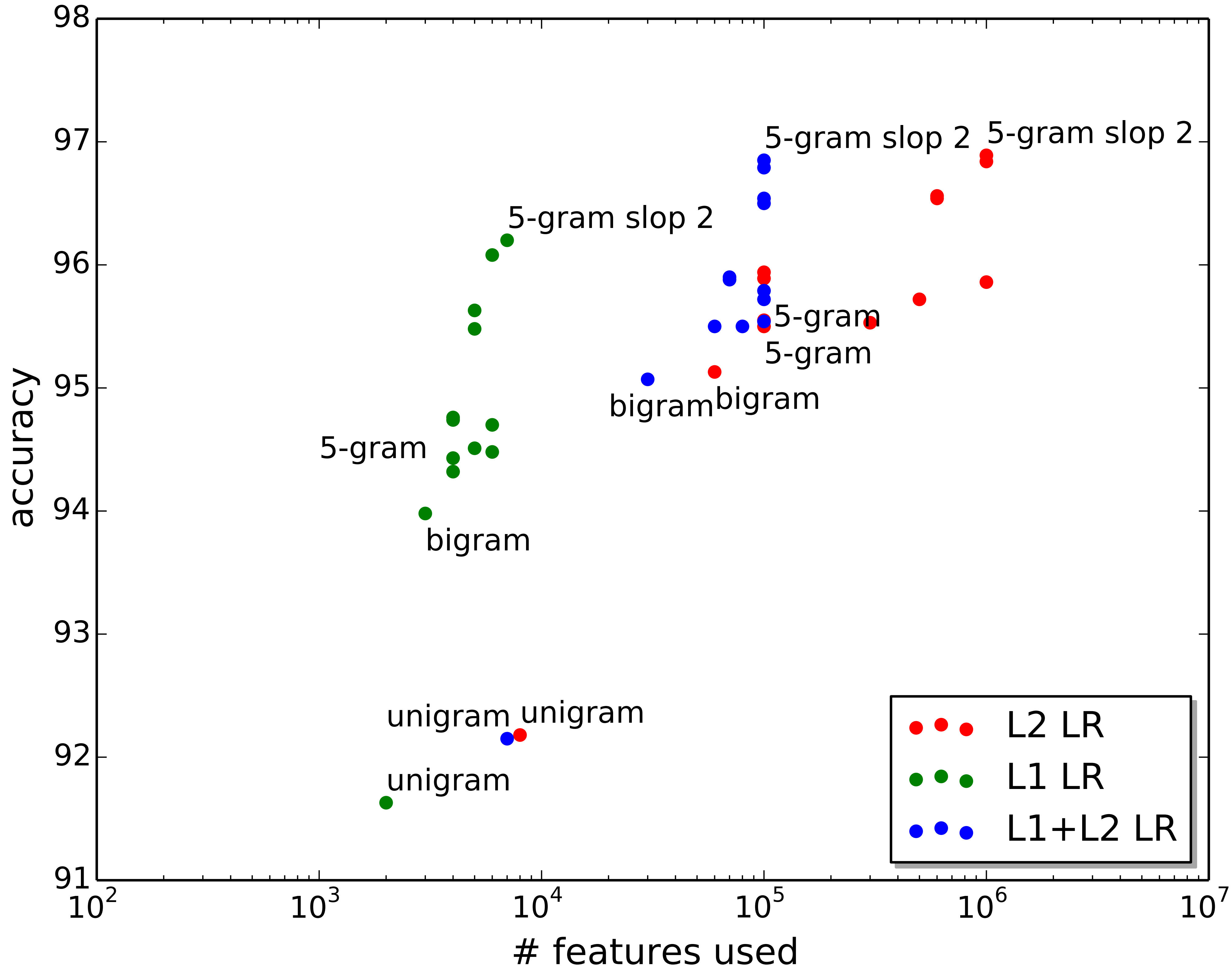
L1 LR



L1+L2 LR

- Blue line: moving from unigrams to bigrams gives substantial improvement
- Blue line: using high-order n-grams gives marginal improvement
- Green and red lines: increasing *slop* from 0 to 1 and 2 gives further improvement
- max # features selected: L2: 10^6, L1: 10^4, L1+L2: 10^5

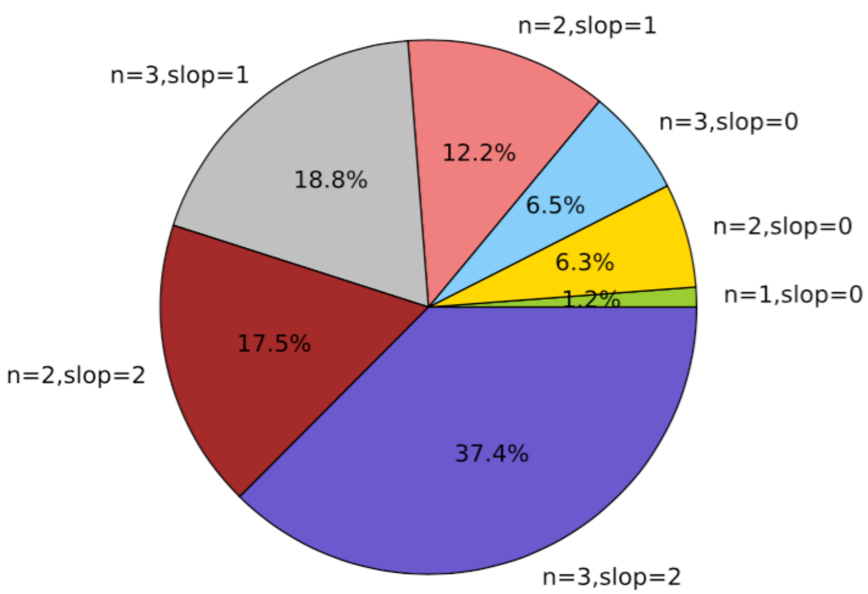
Features Used vs Accuracy



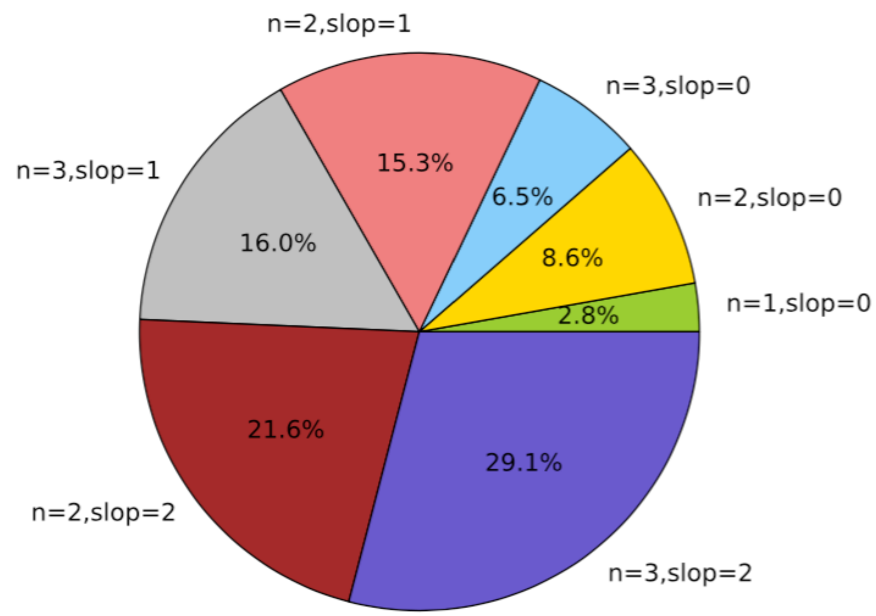
Observations on L1 vs L2

- L2: achieves better overall accuracy
  - Large training sets facilitate parameter estimation
  - Effective handling of correlated features
- L1: produces much smaller models
- L1+L2: good compromise

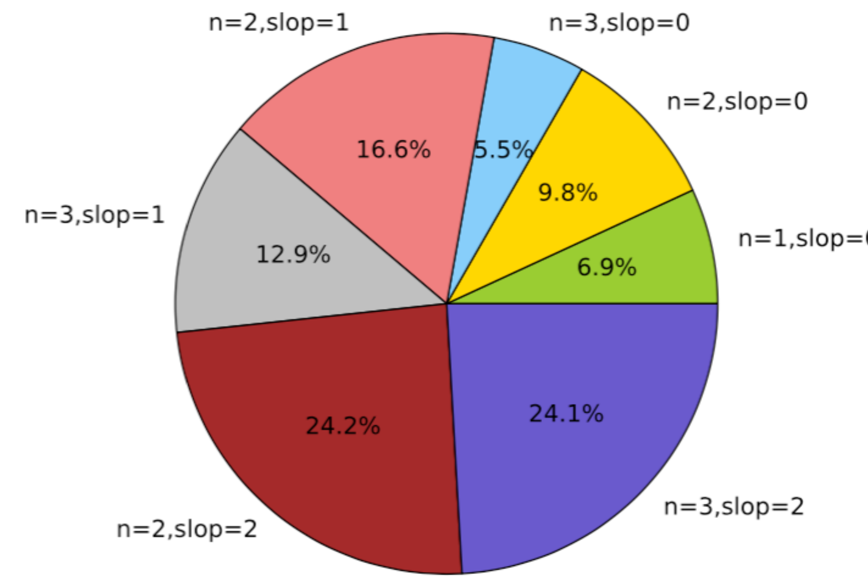
Skip-gram Feature Contribution



all features



selected features



weighted features

- Comparing left with middle: the fraction of unigrams increases;the fraction of *slop* 2 trigrams decreases. Many *slop* 2 trigrams are eliminated by L1.
- In right: The standard n-grams with *slop*=0 only contribute to 20% of the total weight, and the remaining 80% is due to skip-grams with non-zero *slops*.

Comparison with Word Vectors

	skip-gram	word vector
AMAZON BABY	96.85	88.84
AMAZON PHONE	92.58	85.38
IMDB	91.26	92.58 / 85.0

- Word vectors work extremely well on the given test set (92.58%), but poorly on random test sets (85%).

Other Results on IMDB

classifier	features	training documents	accuracy
LR with dropout regularization [21]	bigrams	25,000 labeled	91.31
NBSVM [23]	bigrams	25,000 labeled	91.22
SVM with L2 regularization	structural parse tree features + unigrams [16]	25,000 labeled	82.8
LR L1+L2 regularization	5-grams selected by compressive feature learning [20]	25,000 labeled	90.4
SVM	word vectors trained by WRRBM [6]	25,000 labeled	89.23
SVM	word vectors [15]	25,000 labeled + 50,000 unlabeled	88.89
LR with dropout regularization [21]	bigrams	25,000 labeled + 50,000 unlabeled	91.98
LR	paragraph vectors [14]	25,000 labeled + 50,000 unlabeled	92.58
LR with L2 regularization	skip-grams	25,000 labeled	91.63
SVM with L2 regularization	skip-grams	25,000 labeled	91.71
LR with L1+L2 regularization	skip-grams	25,000 labeled	91.26

- Among the methods which only use labeled data, skip-grams achieved the highest accuracy

Conclusion

- Skip-grams group similar n-grams together, facilitating learning and generalization

- Using skip-grams achieves good sentiment analysis performance

- L1+L2 regularization reduces the number of features significantly while maintaining good accuracy

- Our code will be released soon at: https://github.com/cheng-li/pyramid

Thank You