LING 575
Aspect Based Feature Selection For Review Sentiment Analysis

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Intro

- Create a baseline classifier for sentence level sentiment analysis using MALLET
- Find aspect based features using MALLET LDA
- Do feature selection over unigram features using LDA models

Task

- Restaurant review data (Ganu et al., 2009)
  - Sentence level sentiment annotations with aspects
- Classify sentences as positive, negative, or neutral
- Throw out “conflicted” sentences

Data

- 3400 sentences in total, ~5 per review
  - Each sentence labeled with positive, negative, neutral, or conflicted
  - Each sentence labeled with aspect, such as “food”, “service”, “price”, etc.
- Reviews randomly split into 60/20/20 train, dev, test sets

Outline

- Baseline classifier: MALLET
  - Experiment with features
    - Unigrams, bigrams, removing stop words
    - “not” and “but” shallow analysis
  - Experiment with feature selection
    - Sentiment lexicon
  - Experiment with algorithms
    - MaxEnt, Decision Tree, Naïve Bayes

Baseline Classifier

- Unigram + bigram features, binarized
  - Bigrams didn’t help, so didn’t try trigrams
- MALLET’s --remove-stop-words feature
- Kept “!,.?”

Baseline Classifier

- Shallow structural analysis
  - Replace all words after “but” and “not” with “but_word” and “not_word”
  - No improvement
    - maybe can be improved?

Baseline Classifier

- Sentiment Lexicon (Hu and Liu 2004)
  - Tried two things:
    - In negative sentences, only keep negative words, and vice versa
    - In negative sentences, keep neutral words and negative words, and vice versa
      - In neutral sentences, only keep neutral words

Baseline Classifier

- Sentiment Lexicon
  - Keeping more words helped

Baseline Classifier

- Algorithms (from MALLET)
  - Decision Tree
  - MaxEnt
  - NaiveBayes
- No tuning, but MaxEnt worked best out of the box!

Baseline Results: trainers

U: unigrams; B: bigrams; Bin: binarized; S: stop-words removed;
Lex: sentiment lexicon used; Struct: shallow structure analysis

	Decision Tree		Naive Bayes		MaxEnt	
	Train	Dev	Train	Dev	Train	Dev
U	0.598	0.544	0.852	0.643	0.979	**0.672**
U + Bin	0.598	0.544	0.847	0.637	0.979	0.651
B	0.602	0.548	0.988	0.578	0.994	0.594
B + Bin	0.602	0.548	0.988	0.576	0.994	0.595
U + B	0.601	0.544	0.960	0.639	0.997	**0.672**
U + B + Bin	0.601	0.544	0.960	0.651	0.997	0.661

Baseline Results: lexicon

U: unigrams; B: bigrams; Bin: binarized; S: stop-words removed;
Lex: sentiment lexicon used; Struct: shallow structure analysis

	MaxEnt	
	Train	Dev
U	0.979	0.672
U + Struct	0.983	0.669
U + B + Struct	0.997	0.670
U + Lex	0.984	**0.730**
U + B + Lex	0.998	0.697
U + Struct + Lex	0.987	0.714
U + Bin + Struct + Lex	0.988	0.717
U + B + Bin + Struct + Lex	0.998	0.691

LDA

- Detect topics in data (unsupervised)
- Each document is a mixture of topics
- Find keywords for each topic

LDA

- Use mallet train-topics
  - number of topics = 10; we did not tune hyperparameters
  - can choose word- or phrase-based...
  - “MAP” LDA: split training data into 10 parts based on the most probable topic
  - each part has 145-243 sentences

0 ve place dinner times nyc area side bit time years lunch live restaurant bad romantic small expect st couple

1 service food great prices excellent staff friendly attentive quality decor good atmosphere delicious restaurant wonderful money fun thing makes

2 food place restaurant restaurants love indian thai authentic city favorite cuisine japanese chinese pay places street give neighborhood italian

3 chicken rice fish hot spicy dish sauce thai ordered shrimp special beef rolls fresh dishes soup fried tuna curry

4 delicious menu food dessert portions steak pasta made huge appetizer appetizers ve del fresh large salad order dishes cheap

5 back restaurant night place friends time recommend highly dinner family check friend recommended reviews saturday day coming sushi boyfriend

6 pizza good sum dim taste bagels sushi nyc cold menu places sandwich lobster slice cheese rest overpriced make price

7 table back wait times ca restaurant people asked waiter experience minutes order seated time left group bar make wrong

8 place great good food service pretty spot average atmosphere excellent late lunch cool night perfect found sit date ambiance

9 great wine good worth amazing meal food eat list visit menu deal selection priced price drinks glass decent house

Feature selection

- Assign a score to each token based on its mutual information with “positive” or “negative” labels
- Do a general feature selection, and then do for each of the 10 parts

Feature selection

great not delicious best n't was worst excellent do good just rude slow overpriced attentive no order nothing twice table our bland wonderful to is recommend we perfect seem horrible past although told us try after authentic work that took were average tables oily together annoying disappointment awful watery unless bill section problem tasted loud friendly she asked bring minutes but amazing

0 best i worst twice not cozy level took out the way was go as never once lived years return 's spot first service employees sitting tried noise putting then them also without overpriced his tables come expensive these editorial bucks better an were about been over

1 n't at do great slow friendly attentive and nothing problem money or very something least because am bo should takes visit broke green over lava nyc g times twenty say clean probably commend middle now skeptical seating oh o slightly official distract cake came when

2 no with best be italian one ' not pay much authentic msg lousy using overrated all foods who folks my to would new live call quite why than actually ordering favorite compared simple do out city have indian chinese makes idea many am among definitely great like asian

3 was were oily best bland try dry is since get classic into recommend ordered love small disgusting watery got nothing fun could here delicious a section just and not flavor from tasted even dish there its an would sea seafood where couple i chinese seasoning few

4 delicious n't parisian fondue tasted joke expensive drink ok did main fresh appetizer been steak huge pasta eat selection lot now all would entree was were small great is stinks dip cosette cozy path mozzarella changes medium excuse share after loyalty artisanal

5 back after n't recommend went service the half friend by great finally very door past not about highly again what work experience did worst order entire could disappointment off know while first decided made reservation everyone we for girls pm so has my night

6 the nite best overpriced good food try menu slice th must special sell eaten wish like ever worst nothing busy n't not was you sure ok late there no so in of is nyc it for really when plain out all bagels 's taste a at with family pastrami joe both two went walk snapple

7 go our to back or waitress service great definitely best was never over rude loud small order table all could glasses at promptly night and water understand us awful she someone ca every appetizers begin believe line asked up reservations as conversation 'm enough

8 horrible great good service and not away stay average other be crowd ues sweetness heard should tiffin big late loved if yeah due same is n't very perfect i fact no cost rude took expensive tables around down excellent from did restaurants can lunch been amount

9 not off restaurant such rao nothing know 've dinner amazing least twice italian i great ent rees annoying new disappointed out it to wine well be wait just and worth are month 're when on weird after pay only limited thing wanted could table would without take never

Conclusion

- Unigrams very effective
- MaxEnt works great
- Sentiment lexicon very effective
    - [Hopefully] topic specific feature selection will work even better!