Reducing Label Cost by Combining Feature Labels and Crowdsourcing

Combining Learning Strategies to Reduce Label Cost
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Labels are expensive

- Immense amount of data in the real world
- Often, no corresponding glut of labels
  - Precise labels may require expertise
  - Must ensure training labels have good coverage

Two strategies to mitigate cost

- Leverage unlabeled data in learning

- Find a cheaper way to annotate

Two strategies to mitigate cost

- Leverage unlabeled data in learning
  - **Bootstrapping:** Use your labeled data to generate labels for unlabeled data
  - **Active Learning:** Choose the most useful unlabeled data to label
- Find a cheaper way to annotate
  - **Feature Labels:** Use a heuristic to generate labels
  - **Crowdsourcing:** Get non-experts to provide labels

Feature Labels + Bootstrapping

- Feature Labels
  - Choose features that are highly correlated with labels
  - Remove features from input and use as labels
  - Possibly introduces bias into training data
- Bootstrapping
  - Train a classifier on labeled data
  - Predict labels on unlabeled data
  - Use the most confident predictions as labels

McCallum, Andrew and Nigam, Kamal. Text classification by bootstrapping with keywords, EM, and shrinkage. ACL99

Active Learning + Crowdsourcing

- Active Learning
  - Train a classifier
  - Predict labels on unlabeled data
  - Choose least confident predictions for label acquisition
- Crowdsourcing
  - Provide data to non-experts, reward for labels
  - Few requirements/guarantees about labelers
  - Resulting labels may be noisy, gamed

Ambati, V., Vogel, S., and Carbonell, J. Active learning and crowd-sourcing for machine translation. LREC10

Comparing Learning/Annotation Strategies

- Active Learning
  - Find labels for uncertain instances
- Bootstrapping
  - Find labels for certain instances
- Feature Labels
  - High precision, Low coverage
- Crowdsourcing
  - Low precision, High coverage

Active Bootstrapping

- Input: Feature label rules **F**, unlabeled data, **U** and constants T, k and α
- Initialize **S** by applying feature labels **F** to data **U**
- For t = 1, …, T:
  - Train a classifier on **S**
  - Predict labels on **U**
  - Add top-k most certain positive predictions to **S**
  - Add top-k most certain negative predictions to **S**
  - Add crowdsourced responses to top-αk uncertain predictions to **S**
  - **U** = **U** – **S**
- Output: Classifier trained on **S**

Evaluation on Twitter dataset

- Task: Sentiment Analysis (happy/sad tweets)
- Data: 77920 normalized* tweets originally containing emoticons (6/2009-12/2009)
- Evaluation Set: 500 hand-labeled tweets
- Feature labels: happy and sad emoticons from Wikipedia
- Crowdsourcing: HIT on Amazon's Mechanical Turk platform. Use known evaluation set labels to validate results
- Active Learning/Bootstrapping: Use MEGAM maximum entropy classifier label probabilities

Yang, Jaewon and Leskovec, Jure. Patterns of temporal variation in online media. WSDM11

Wikipedia: List of Emoticons http://en.wikipedia.org/wiki/List_of_emoticons

Daumé III, Hal. http://www.cs.utah.edu/~hal/megam/

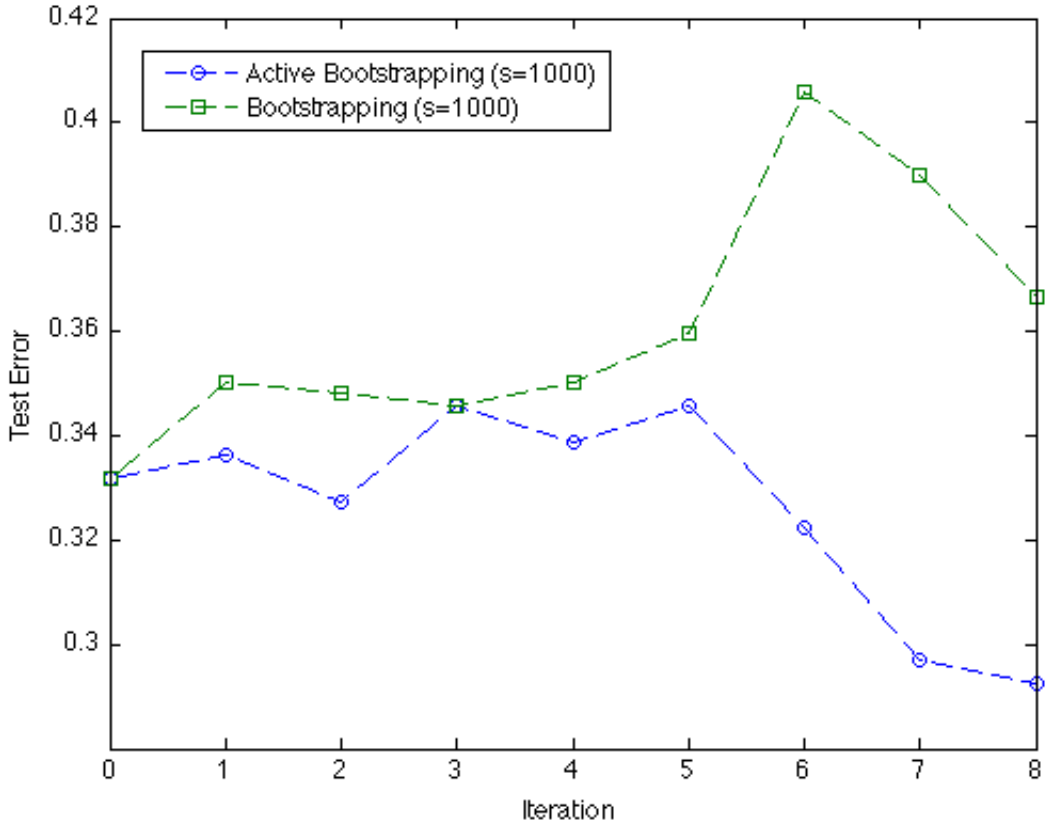
Experiments on Twitter dataset

- Compare different approaches:
  - Feature Labels + Bootstrapping
    - Start with seed set of 1K, 2K, 10K feature labels
    - Add 10% of seed set in each iteration
  - Crowdsourcing + Bootstrapping
    - Start with 2000 crowdsourced labels (1000 instances)
    - After validation, 670 labels
    - Add 200 new labels in each iteration
  - Active Bootstrapping (k=50, α=2)
    - Start with 1000 labels, add 100* crowdsourced and 100 bootstrapped labels in each iteration

Results:

Active Bootstrapping vs. Feature Labels + Bootstrapping

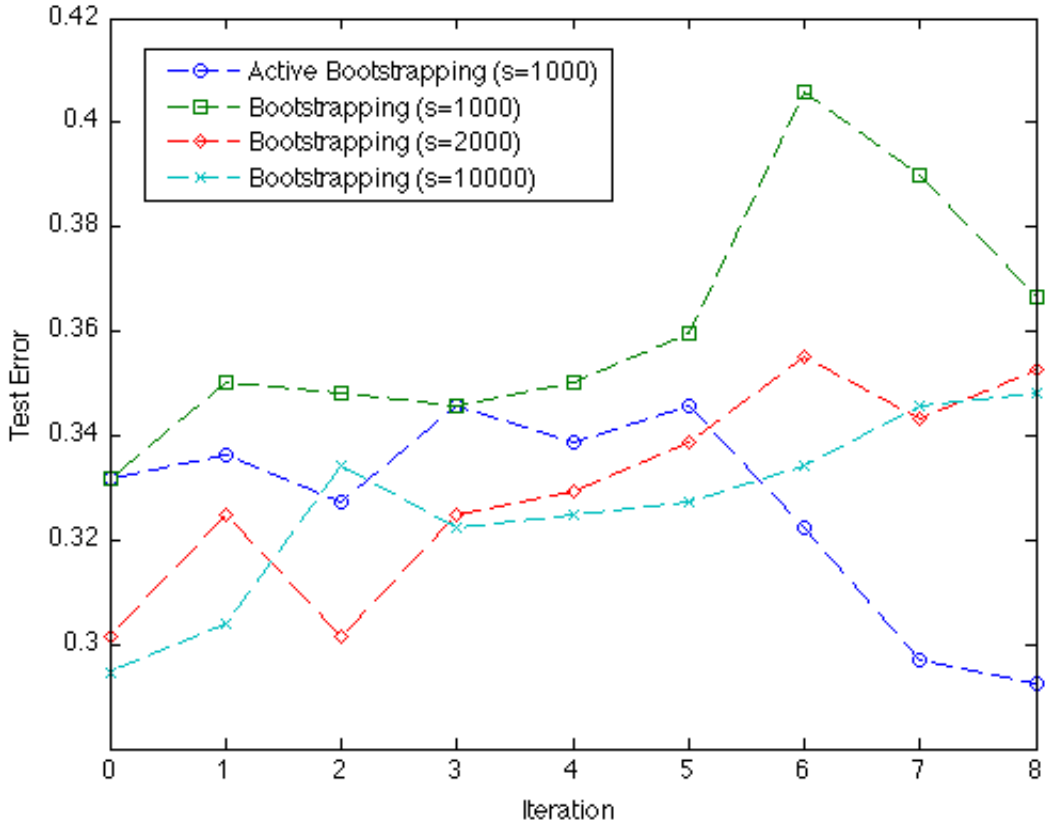
- Same amount of data per iteration
- Active Bootstrapping outperforms Feature Labels + Bootstrapping, at minimal cost ($16)



Results:

Active Bootstrapping vs. Feature Labels + Bootstrapping

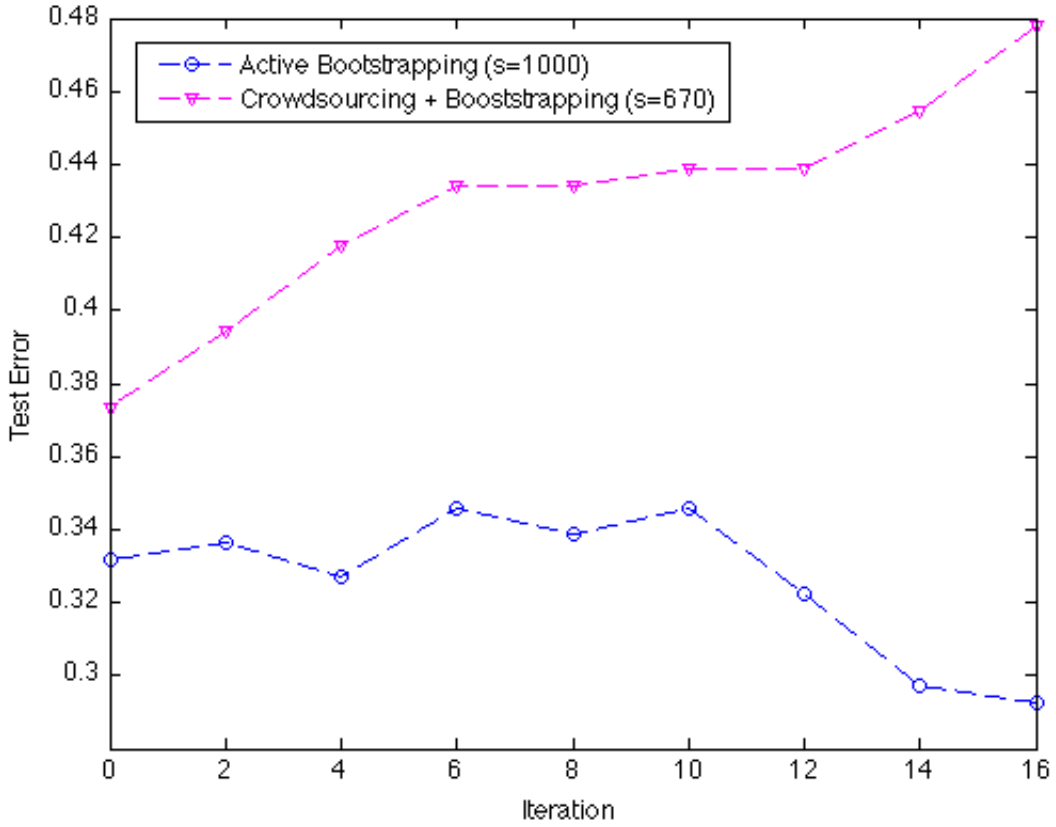
- Even with additional starting data, Feature Labels + Bootstrapping starts well but is eventually overcome by Active Bootstrapping



Results:

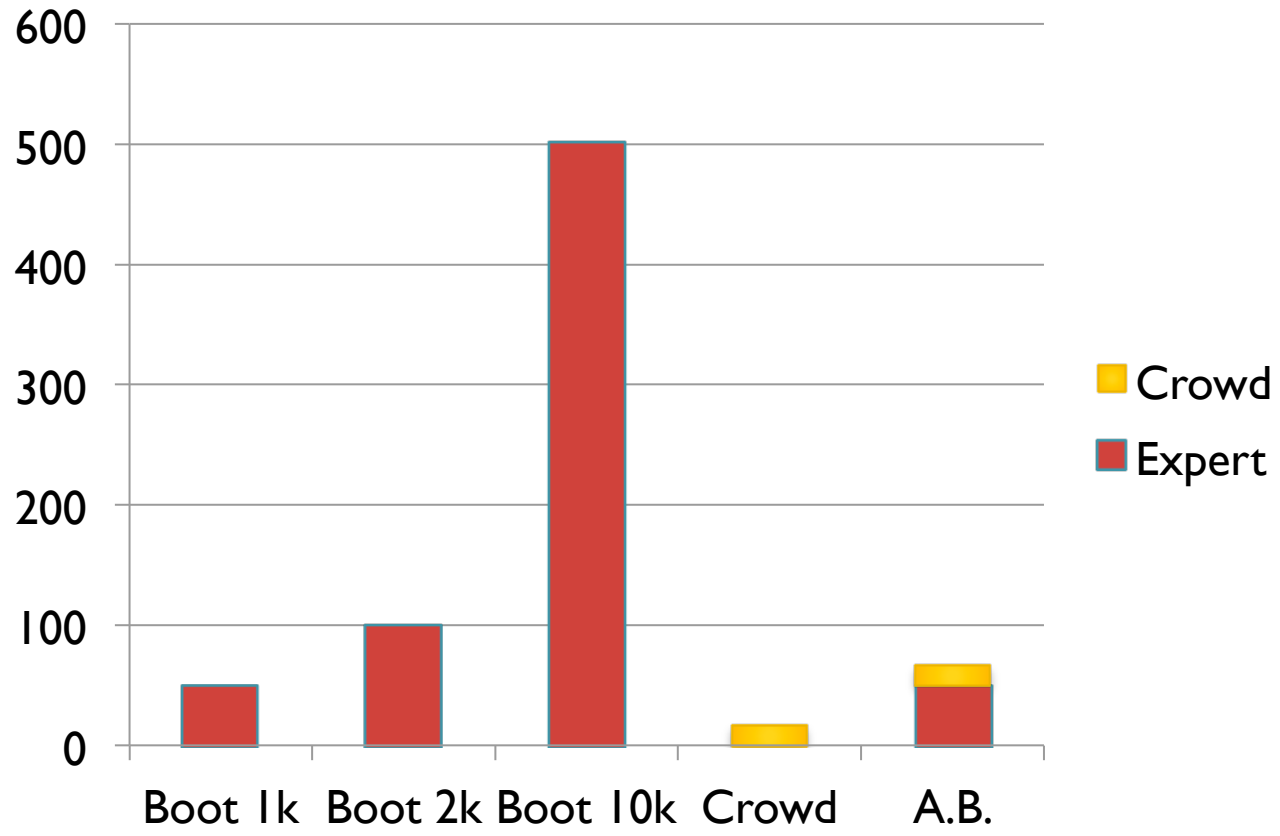
Active Bootstrapping vs. Crowdsourcing + Bootstrapping

- Both methods cost about the same ($16), but Active Bootstrapping clearly outperforms.



Cost

- Active Bootstrapping combines the best of both worlds:
  - Minimal time/expense from domain expert (to create feature labels)
  - Crowdsource the rest



Results:
Summary

Method	**Err, I0**	**Err, I8**
Feature Lables, 1K	.332	.367
Feature Lables, 2K	.302	.353
Feature Lables, 10K	**.295**	.348
Crowdsource, 2K	.374	.478
Active Bootstrapping	.332	**.292**

Thank You!

- Reduce label cost by combining strategies
- Introduce algorithm, Active Bootstrapping:
  - Combines complementary annotation strategies (feature labels and crowdsourcing)
  - Combines complementary learning strategies(bootstrapping and active learning)
- Evaluate on a real-world dataset/task (sentiment analysis on Twitter), show superior results

Read the full paper: http://bit.ly/activebootstrapping

Questions?