ML-INDIA

ML-India our attempt at spurring the machine learning and data science ecosystem in India.

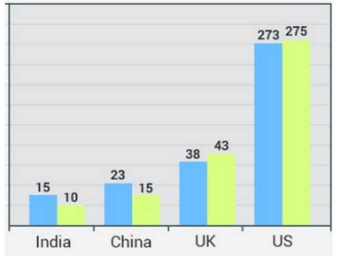
Activities

Meetups: We hold ML meetups where ML enthusiasts discuss and brainstorm ideas. Read more here.

Interviews: Top ML researchers and practitioners from academia and industry discuss their work.
Read our interview with Dr. Mayank Vatsa from IIITD.

Data Sets: Open Indian data sets for researchers and practitioners to help them with easy access to data. Check it out!

Data Angels: Support for budding and innovative ML/AI start-ups. Read more here.



Conference Analysis: Yearly analysis from top conferences to track the performance of Indian ML research community. Check out NIPS 2015.

Co-founders

Varun Aggarwal

Shashank Srikant

Varun is the co-founder of Aspiring Minds, one of the world's largest machine learning driven employability assessment company.

Shashank is a senior research and development engineer at Aspiring Minds.

Our organizers for the Gurgaon and Bangalore chapter meetups

- Bhanu Pratap Singh: Research and Development Engineer, Aspiring Minds
- Sritulasi Edupuganti: Software Development Lead at XAMCHECK

Relevant Resources

- For an introduction to machine learning and its importance, click here.
- Data Angels: India's first angel initiative to encourage AI-backed technologies
- Read a machine learning paper on ‘A Machine Learning Approach to Twitter User Classification by Pennacchiotti et al’.
- Check out our list of research groups and people involved in ML.
- Click here to see a list of ML companies in India.
- Do you have any questions? Write to us!

ml-india.org

Join our mailing list for the latest updates on our activities!

ML India

* A place, an effort to catalyze the Machine Learning ecosystem in India involving students, researchers, institutions & corporations(http://ml-india.org/)

* Maintained by a group of Machine Learning and Data Science enthusiasts

Varun Aggarwal, Co-founder, Aspiring Minds

Shashank Srikant, Researcher, Aspiring Minds

Bhanu Pratap, Researcher, Aspiring Minds

Harsh Nisar, Researcher, Aspiring Minds

Sritulasi Edpuganti(Bangalore chapter), Co-founder, Dolphino

Agenda

* Intro to ML
* Intro to ML Algorithms used in paper
* Paper Highlights and Summary
* Discussion

What is Machine Learning?

* Herbert Simon (Turing award 1975, Nobel prize in Economics 1978)- “Learning is any process by which system improves performance from experience”
* More formally, Tom M. Mitchell - "A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P if its performance at tasks in T, as measured by P, improves with experience E”

What is Machine Learning?

* Is disrupting AI bigtime...
* Widely used in everyday life, without us even knowing it
* Important to understand intuition - handy cross domain skill

Applications of ML

* Self Driving Cars (Watch: https://www.ted.com/talks/chris_urmson_how_a_driverless_car_sees_the_road?)
* Face Recognition (Ex: Facebook Autotagging)
* Speech Recognition(Ex: Siri, Cortana)
* Personal Recommendations (Ex: Netflix, Amazon,...)
* Efficient Web Search(Ex: Google, Bing,...)
* And many more..........

Supervised Learning

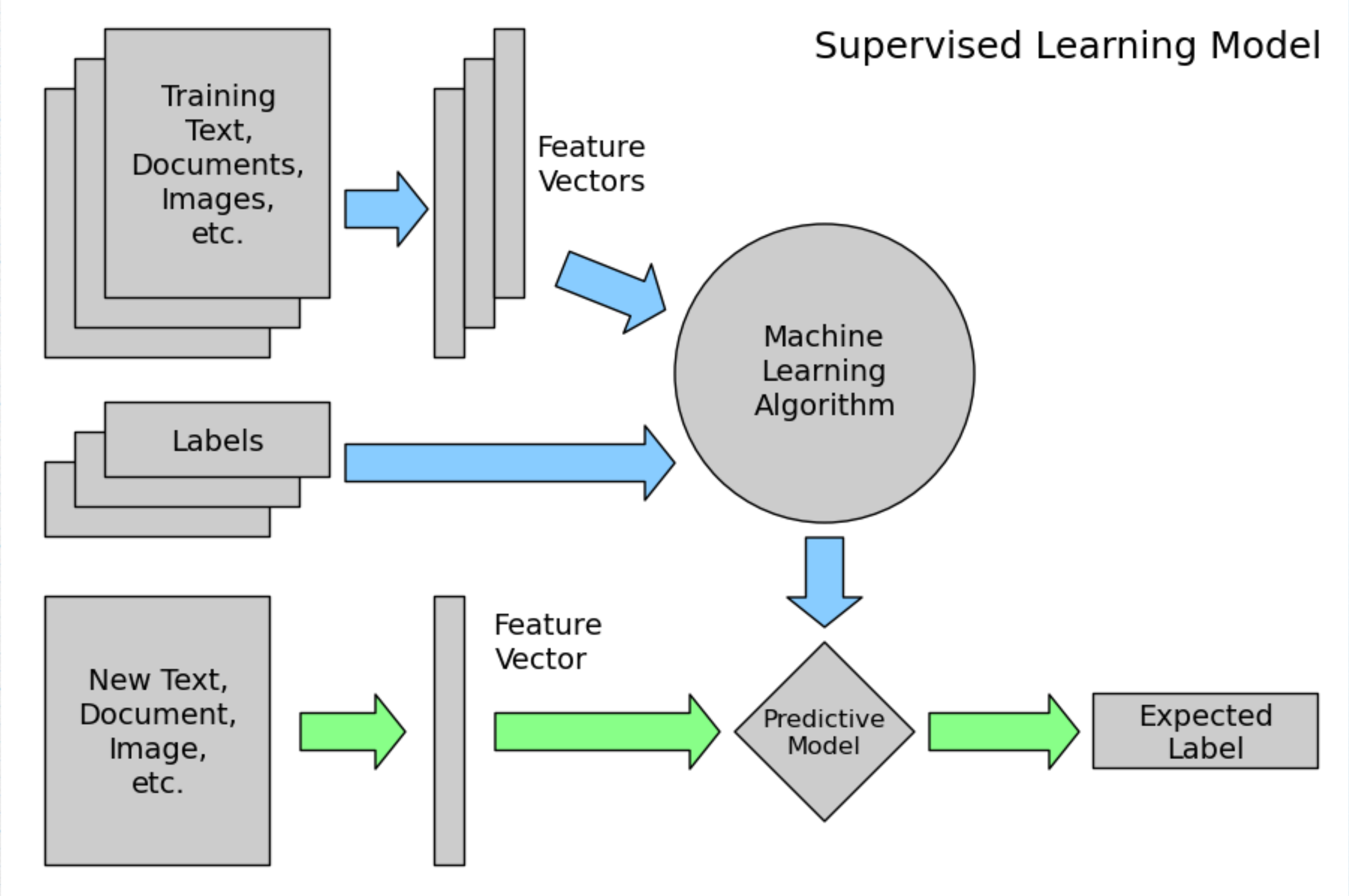


Image credit: Astroml blog

ML Jargon

* Features/Input data
* Labels/Observed values
* Precision
* Recall
* F-measure
* Cross Validation

Supervised Learning

One key research area in machine learning is to find the right features for a given problem.

Supervised Learning

Number of different models and learning techniques for these model

* Linear Models
* Ridge/LASSO
* Polynomial Models
* Neural Networks
* Deep/convolutional networks
* SVMs
* Decision trees
* Ensemble models
    * Boosting/bagging
        * Gradient boosted Decision Trees (more on this later)

Unsupervised Learning

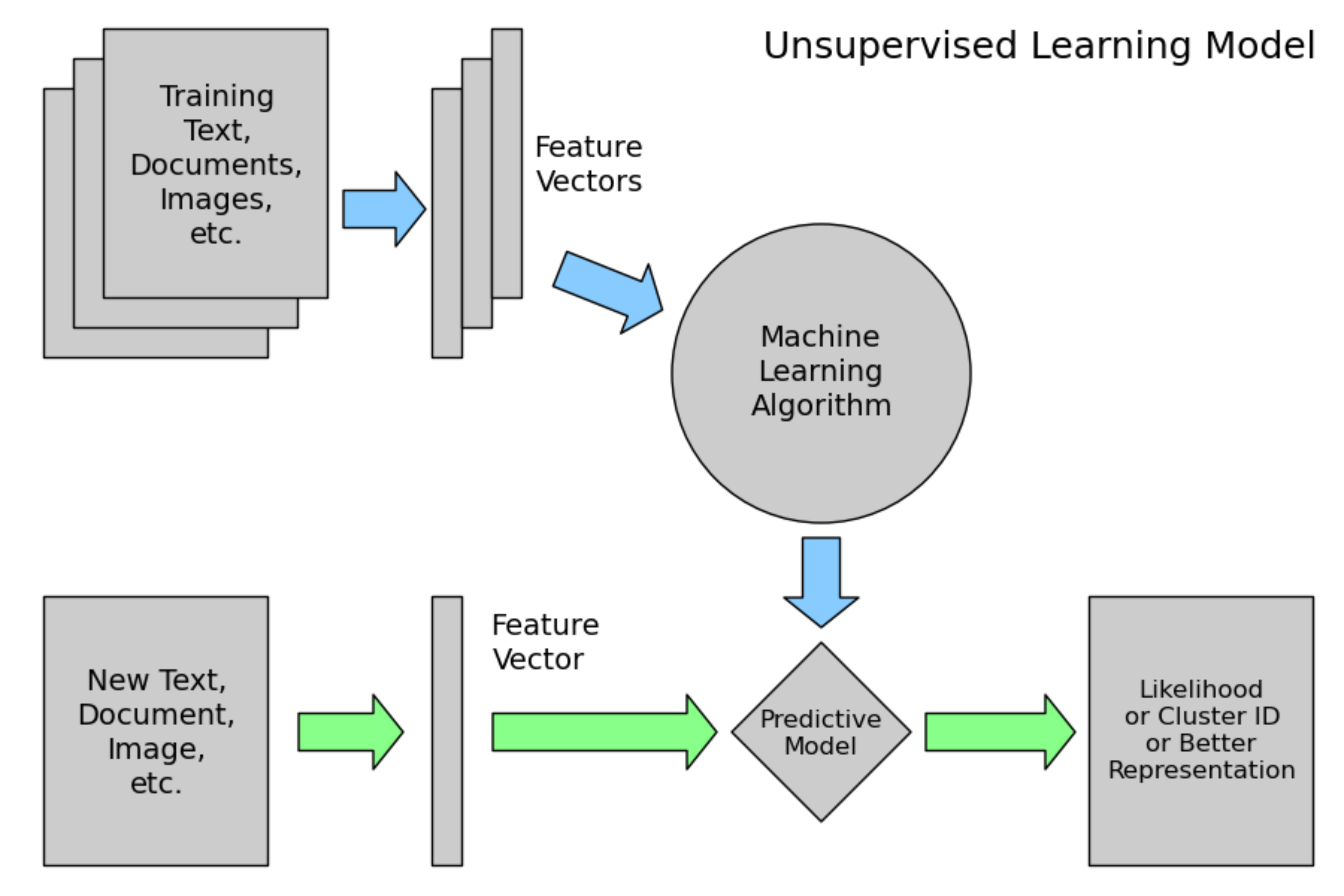


Image credit: Astroml blog

Unsupervised Learning

* Clustering (K-means, hierarchal,...)
* Singular value decomposition
* Dimensionality Reduction
    * Principal Component Analysis(PCA)

Algo/models used in paper

* Gradient Boosted Decision Tree (ML Algo)
* Latent Dirichlet Allocation (LDA - a kind of topic modelling technique)

Gradient Boosted Decision Tree

Friedman 2001, Greedy function Approximation: A Gradient Boosting Machine

* Effective, Off-the-shelf method for predictive models with high accuracy
* Ensemble of weak learners , usually Decision Trees.
* In gradient boosting, model assumes an additive expansion

$$F(x, \beta, \alpha) = \sum_{i=1}^{n} \beta_i h(x, \alpha_i)$$

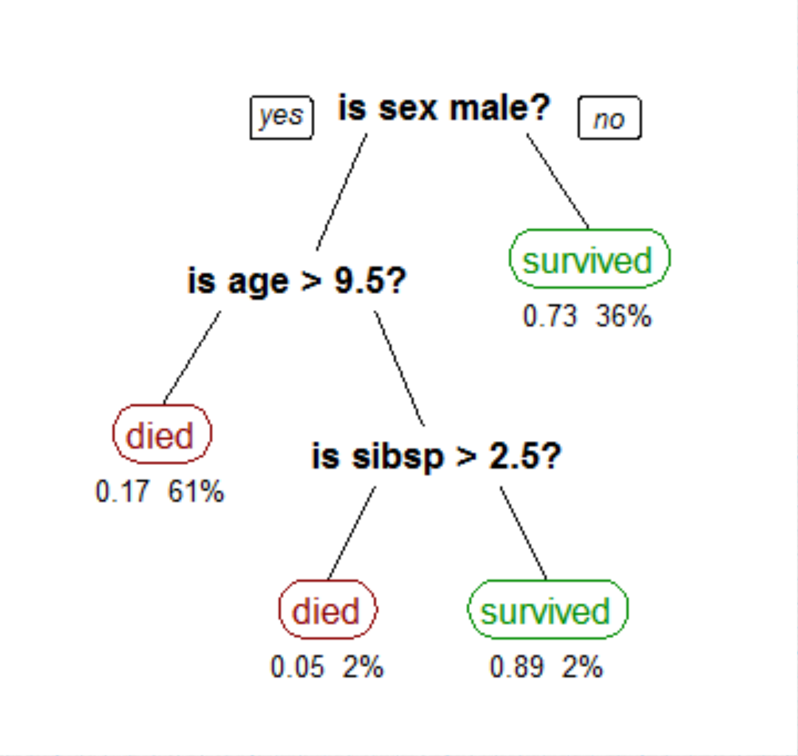
(x,y)-Input labelled features
F(x) - Function to estimate
h- weak learners
B- (To compute), the weight that a given classifier has in context of ensemble

Gradient Boosted Decision Tree

* Intuitively, we iteratively build a sequence of predictors, and our final predictor is a weighted average of these predictors
* At each step, we focus on adding an incremental classifier that improves the performance of the entire ensemble.
* Good resources
  * http://tullo.ch/articles/gradient-boosted-decision-trees-primer/
  * http://www.analyticsvidhya.com/blog/2015/09/complete-guide-boosting-methods/

Gradient Boosted Decision Tree

* Good resource lo learn Decision Tress - http://www.r2d3.us/visual-intro-to-machine-learning-part-1/
* A flow chart like tree structure
* Internal node denotes test on attribute
* Branch represent outcome of the test
* Leaf nodes represent class labels or class distributions



Source:Wikipedia

Latent Dirichlet Allocation(LDA)

* In context of paper - a variant of LDA is used to calculate linguistic features for GBDT.
* It is a topic modeling technique
* It is a way of automatically discovering topics from unstructured text.

Latent Dirichlet Allocation(LDA)

Example: Suppose we have following sentences

- I like to eat broccoli and bananas.
- I ate a banana and spinach smoothie for breakfast.
- Chinchillas and kittens are cute.
- My sister adopted a kitten yesterday.
- Look at this cute hamster munching on a piece of broccoli.

LDA will produce result like this

- Sentences 1 and 2: 100% Topic A
- Sentences 3 and 4: 100% Topic B
- Sentence 5: 60% Topic A, 40% Topic B
- Topic A: 30% broccoli, 15% bananas, 10% breakfast, 10% munching, ... (topicA - about food)
- Topic B: 20% chinchillas, 20% kittens, 20% cute, 15% hamster, ... (topicB - cute animals)

Source: Edwin chen's Blog (He is a great ML guy to follow)!

Twitter User Classification (Marco Pennacchiotti, Ana-Maria Popescu)

Highlights

* Problem to solve - Automatically infer user attributes like Political Affiliation, Ethnicity, Affinity to a business
* Features used
    * Profile features (Name, location, bio,...)
    * Tweeting behavior (Avg no of tweets per day, number of replies,....)
    * Linguistic features (Prototypical words, Prototypical Hashtags, topic modeling, sentiment words)
    * Social network (replies, retweets,...)
* Learning Algo used - Gradient Boosted Decision Trees
* Results :
    * User Political Affiliation classified into Republicans/Democrats (Precision:0.894±0.007)
    * User Ethnicity classified into African-American/Not (Precision:0.646±0.017)
    * User classified for his affinity to starbucks (Precision: 0.763±0.021)
* Takeaways
    * Linguistic features (esp, topic-based) are proved consistently reliable across these classification tasks
    * Explicit social network features are valuable

Background

How many of you use ?

Significant Improvements can be made to user experience by knowing demographic attributes, interests,..etc of a user

Recommendations can be given w.r.t which users to follow, what posts to read,...etc.

Related Work

* Twitter user attribute detection. (Rao et al. 2010)
    - simple features like N-grams
    - Sociolinguistic features (presence of emoticons)
    - User network Statistics (No of followers)
    - Communication behavior(Retweet frequency)

  are used for user attribute detection.

Learning Algo & Features

- **Learning Algo:** Gradient Boosted Decision Trees (Friedman 2001)
- **Profile features (PROF)**
  - Pilot study to access direct use of profile info (for gender and ethnicity classification tasks)
    - Corpus - 14M users
    - Technique - 30 regular expressions on Bio field

      ```
      (I|i) (m|am|'m) [0-9]+(yo|year old)
      white (man|woman|boy|girl)
      ```

    - Results - could find ethnicity of <0.1% users, gender of 80% users. **Low Accuracy**
  - Though profile fields don't contain good quality data, it can be used for bootstrapping training data. Some features derived are
    - length of username
    - use of avatar picture
    - no of followers...etc

Learning Algo & Features

* Tweeting behavior features - useful for constructing model of user. 20 BEHAV features like
    - No of tweets
    - No & fraction of retweets
    - urls/tweet
    - avg no of #
    - avg time and std. between tweets ,......

Learning Algo & Features

* Linguistic features (features extracted from a tweet)
    - Prototypical words/ Proto words(LING-WORD)
        - classes can be described by these words
        - young people - dude, lmao,...
        - republicans - healthcare,..
        - probabilistic model for automatically extracting proto words
        - 2 Features derived:
            - ✦ score based on no of proto words used by user
            - ✦score based on number of proto words belonging to a class- for that user

Learning Algo & Features

- Prototypical Hashtags (LING-HASH)
  - Hypothesis: users from same class might like similar topics. Topics can be derived from Hashtags they used
  - Features calculated similar to LING-Word after finding top hashtags used by users
- Generic LDA (LING-GLDA)
  - Adaptation of original LDA; documents are replaced by users
  - Users are represented as multinomial distribution of topics
  - users = words of tweet
  - how used in classification - Democrats higher prob of talking about social reforms, Republicans higher prob of talking about oil drilling
  - General topics returned - soccer, music, politics

Learning Algo & Features

- Domain-specific LDA(LING-DLDA)
  - users from a specific domain like republicans, democrats
  - Domain specific topics returned - reforms, conservative approach
- Sentiment Words(LING-SENT)
  - Hypothesis: one class can have a majority opinion on a topic, which is different from other class
  - Ronald Reagan - Republicans(+), Democrats(-)
  - Manually collect set of terms for classes and find sentiment of user w.r.t those terms

Learning Algo & Features

* Social Network Features
  * Friend accounts(SOC_FRIE) - Democrats following democrats
    * Find protypical friend accounts (similar technique used for proto words)
    * For each porto-friend account, set value to 1 if user follows, 0 otherwise
  * Prototypical replied (SOC-REP) and retweeted (SOC-RET)
    * Hypothesis : users belonging to same class, reply/retweet messages from specific accounts
    * Features calculated similarly as Ling-word/Ling-Hash

Experimentation Results

System	PREC	REC	F-MEAS
democrats-B1	**0.989**	0.183	0.308
democrats-B2	0.735	0.896	0.808
democrats-FULL	0.894‡	**0.936**♭	**0.915**♭
republicans-B1	**0.920**	0.114	0.203
republicans-B2	0.702	0.430	0.533
republicans-FULL	0.878‡	**0.805**♭	**0.840**♭
ethnicity-B1	**0.878**	0.421	0.569
ethnicity-B2	0.579	0.633	0.604
ethnicity-FULL	0.646‡	**0.665**♭	**0.655**♭
starbucks-B1	**0.817**	0.019	0.038
starbucks-B2	0.747	0.723	0.735
starbucks-FULL	0.762	**0.756**♭	**0.759**♭

Overall classification results

Lets Discuss.....