E6895 Advanced Big Data Analytics Lecture 5:

Social and Cognitive Analytics

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IBM SMISC Team Overview

**Goal 1:** Detect, classify, measure and track the
(a) formation, development, and spread of ideas & concepts (memes)
(b) purposeful or deceptive messaging and misinformation

**Goal 2:** Recognize persuasion campaign structures and influence operations across social media sites and communities

**Goal 3:** Identify participants and intent, and measure effects of persuasion campaigns

**Goal 4:** Counter messaging of detected adversary influence operations

53+ papers published, accepted, & submitted
12+ patents filed
ACM CIKM 2012 Best Paper Award
IEEE BigData 2013 Best Paper Award
PNAS Cover Article Jan 2013
Science (1)
Nature (2)

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**Approach: Modeling, Tracking and Affecting Information Dissemination in Context**

**Thrust 1.** Modeling Information Dissemination in Context:
Models of Trust and Social Capital, Information Morphing, Persuasiveness and Competition of Memes, Dynamics of Social Influence

**Thrust 2.** Detecting and Tracking Information Dissemination in Context:
Detecting Malicious Info Propagation, Evolution History and Authenticity of Multimedia Memes,

**Thrust 3.** Affecting Information Dissemination in Context:
Automated Generation of Counter Messaging, Influencing the Outcome of Competing Memes and Counter Messaging
What Affects Propagation Behavior?
– Computational Discovery of Social Cognitive Essence

Actionable Applications
- Anomaly Detection
- Live Monitoring
- Flow Manipulation
- Predictive Visualization
- Auto-Counter Messaging
- Intranet-Social-Media Action

Inferred Cognitive Traits
- Personality
- Needs
- Value
- Trustworthiness

Inferred Social Network Traits
- Roles
- Dynamic Analysis
- Topological Analysis
- Location Analysis

Analytics & Predictive Models

Social Media Posts

Inferred Social Network Traits
(Human Essential)
- Info Reasoning & Morphing
- Visual Sentiment

Inferred Social Network Traits
(Human Dynamic)
- Emotional State
- Contextual Behavior

(Colourful小镇)

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IBM SMISC Software Architecture

Social Media Data

Memes Persuasiveness in Multiple Networks

Social Content Analysis

Topic Modeling

Information Morph

Social Capital Modeling

Behavioral Modeling

Emotion Analysis

Location Analysis

Role Discovery

Network Controllability & Observability

Visual Manipulation Modeling & Detection

Visual memes evolution models

Social network models

Real-time Large-scale Social Media Mining System

Real-time Large-scale Social Media Mining Algorithms

Content models

Behavioral models

Social Mining Architecture

E6895 Advanced Big Data Analytics — Lecture 5

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Thrust 1. Modeling Information Dissemination in Context:
- Task 1.1. Computational Modeling of User Dynamic Behavior
- Task 1.2. Computational Models of Trust and Social Capital
- Task 1.3. Information Morphing Modeling
- Task 1.4. Persuasiveness of Memes
- Task 1.5. The Observability of Social Systems
- Task 1.6. Culture-Dependent Social Media Modeling
- Task 1.7. Dynamics of Influence in Social Networks
- Task 1.8. Understanding the Optimal Immunization Policy
- Task 1.9. Modeling and Identification of Campaign Target Audience
- Task 1.10. Modeling and Predicting Competing Memes

Thrust 2. Detecting and Tracking Information Dissemination in Context:
- Task 2.1. Real-Time and Large-Scale Social Media Mining
- Task 2.2. Role and Function Discovery
- Task 2.3. Detecting Malicious Users and Malware Propagation
- Task 2.4. Emergent Topic Detection and Tracking
- Task 2.5. Detecting Evolution History and Authenticity of Multimedia Memes
- Task 2.6. Synchronistic Social Media Information and Social Proof Opinion Mining
- Task 2.7. Community Detection and Tracking
- Task 2.8. Interplay Across Multiple-Networks

Thrust 3. Affecting Information Dissemination in Context:
- Task 3.1. Crowd-sourcing Evidence Gathering to Formulate Counter-messaging Objectives
- Task 3.2. Delivery and Evaluation of a Counter-messaging Campaign
- Task 3.3. Optimal Target People Selection
- Task 3.4. Automated Generation of Counter Messaging
- Task 3.5. User Interfaces for Semi-Automatic Counter Messaging
- Task 3.6. Controlling the Dynamics of Influence in Social Networks
- Task 3.7. Influencing the Outcome of Competing Memes and Counter Messaging
Inferring Cognitive Traits: Human Essentials

– Personality
– Needs
– Value
– Trustworthness / Trustingness
– Influence
Deriving Personality

Big5 Personality (OCEAN)

- Extraversion: outgoing/energetic vs. solitary/reserved

- Neuroticism: sensitive/nervous vs. secure/confident

- Openness: inventive/curious vs. consistent/cautious

- Agreeableness: friendly/compassionate vs. cold/unkind

- Conscientiousness: efficient/organized vs. easy-going/careless
Deriving Personality

- Mapping text to psycholinguistic category (LIWC) to BIG 5 Personality [Yakoni '10]: 694 bloggers; 66 LIWC categories; ~2,500 words

- We extended the # of words to about 30,000 by combining with WordNet

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<th>Trait</th>
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<th>Top 20 words</th>
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<td></td>
<td></td>
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<td></td>
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<td></td>
<td></td>
<td>completed (-0.18)</td>
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<td>Agreeableness</td>
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<td>spring (0.25), porn (-0.25), walked (0.23), beautiful (0.23), staying</td>
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<td>(0.23), felt (0.23), cost (-0.23), share (0.23), gray (0.22), joy (0.22),</td>
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<td>Conscientious</td>
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<td></td>
<td></td>
<td>(0.19), utter (-0.19), it's (-0.19), extreme (-0.19), deck (0.18)</td>
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</tbody>
</table>
Deriving Needs

What do we model

- 12-dimension needs

[Ford, 2005]
Collecting Crowd’s Textual Description of Needs

• “Please describe three things that you want to get or need to do the most, and explain why you want or need them. Please be as honest as possible.”
• Minimal requires 60 words, average written 103 words
• Some examples:

1. I need to pay off all my credit card debt by next year. I’m cutting cost wherever I can to help pay off these debts. This will help get me more financially stable. 2. I want to take a vacation to Florida. This also requires saving and cutting costs. I haven’t had a vacation in a long time. 3. I want to lose weight and get healthy. There are sports that I would like to get back into and can’t with my current weight.

1. I want to go running again. I went through a lot of trauma a year ago, and it was reinforced by a couple of troubling incidents that have happened more recently. I find that I can’t go out without being paranoid about who’s around and anticipating that I’ll get attacked and humiliated again. But I so miss the freedom of running. I miss moving my body, my limbs, and my quick responses to challenges that pop into my head when I’m running. I want to get back into it. 2. I need to learn to trust people. I think that everyone has an ulterior motive or is just using me for favors I’ll do for them. These thoughts pop into my head when people are making sincere confessions of emotion, and I still don’t trust them. I would have more friends if I trusted people more. It’s good to be cautious and skeptical, but skepticism needs to be rational. 3. I want to start some kind of company that serves my community. Hair, clothing, whatever. I think it would be fun and would be an outlet for me to 1) meet people and 2) express my creativity and love for fashion.

I want to get an iPhone. I love latest phones with latest features. I want to study more and more. I want to be on the highest rank ever and want to earn a lot more than average. I want to have my own car. I want to drive more and more as I love driving :) I want to have a world tour as I love traveling a lot. I want a lot of things in my life to be done sooner.
Current Results of Needs Detector

- Large-scale crowd-sourced needs scores and text descriptions from over 2800 people on MTurk
- 12 dictionaries for each need dimension
- Use TF-IDF and Elastic-Net regularized generalized linear model for regression.
- Prediction (from one’s tweet) for certain dimensions is better than others
  - cross-validation on collected ground-truth
  - Ideal, Closeness, Excitement, Self-expression, Curiosity, Harmony

Dictionary derived for “Ideals”
Positively correlated: accomplish, chauffeur, goal, license, special...
Negatively correlated: bad, fix, half, minimum, mix, ugly, wrong, obvious, ...

![Chart showing Needs Model Quality]

R^2 values for different dimensions.
Deriving Value

• Why model value
  – Values motivate people and guide their actions
  – Values transcend specific actions and situations

[Schwartz 2006]
Current Results of Value Detector

• Data
  – 800 Reddit users, each with at least 100 posts

• Dependent Variables
  – 4 high-level value dimensions and 10 low-level value dimensions as measured by established questionnaires

• Predictive Variables
  – 68 LIWC dimensions, each representing uses of a particular word category (e.g. self reference, positive feelings, family, money)
  – Number of posts, sentences per post, posts per sentence
  – Up votes and down votes the user got from other users

• Predictive Modeling
  – Regression and correlation analysis

• Regression strength

<table>
<thead>
<tr>
<th>Value Dimensions</th>
<th>R2 of Linear Regression</th>
<th>Correlation between the Regressed Value and the True Value</th>
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<tr>
<td>Self-Transcendence</td>
<td>17.0%</td>
<td>0.39</td>
</tr>
<tr>
<td>Self-Enhancement</td>
<td>13.8%</td>
<td>0.35</td>
</tr>
<tr>
<td>Conservation</td>
<td>15.4%</td>
<td>0.37</td>
</tr>
<tr>
<td>Openness-to-Change</td>
<td>18.1%</td>
<td>0.41</td>
</tr>
<tr>
<td>Hedonism</td>
<td>18.2%</td>
<td>0.41</td>
</tr>
</tbody>
</table>

• Classification accuracy

<table>
<thead>
<tr>
<th>Value Dimensions</th>
<th>Classifier Achieving the Highest AUC</th>
<th>AUC</th>
<th>TPR</th>
<th>TNR</th>
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<tbody>
<tr>
<td>Self-Transcendence</td>
<td>Random Forest</td>
<td>.60</td>
<td>.67</td>
<td>.50</td>
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<td>Self-Enhancement</td>
<td>REPTree</td>
<td>.56</td>
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<td>.57</td>
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<td>Conservation</td>
<td>Logistic Regression</td>
<td>.59</td>
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<td>Openness-to-Change</td>
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<td>Hedonism</td>
<td>Logistic Regression</td>
<td>.61</td>
<td>.53</td>
<td>.63</td>
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</table>
Assessing Inferred Traits from Tweets

• Participants
  – 256 IBMers who have twitter presence with at least 200 tweets

• Procedure
  – Participants took three sets of psychometric tests of Big 5, basic values, and fundamental needs
  – Participants rated how well each type of the derived trait matches with their perceptions of themselves
Deriving Traits from Tweets - Results (1)

• Comparing Derived Traits with User Perception
  – All ratings are above 3 (“mostly matched”) out of 5 (“perfectly matched”).
  – The overall ratings
    • Big 5: $u=3.4$, $sd = 1.14$
    • Values: $u= 3.13$, $sd = 1.17$
    • Needs: $u= 3.39$, $sd = 1.34$
Deriving Traits from Tweets - Results (2)

- Comparing Derived Traits with Psycho-Metric Scores
  - Correlational analysis of a trait profile (considering all dimensions together within one type of trait)
    - RV-Coefficient Correlation Test
  - Percentage of population with significance are 80.8%, 98.21%, and 86.6% for Big 5 personality, basic values and needs.

![Graphs showing correlations between derived traits and psycho-metric scores for Personality, Values, and Needs.](chart.jpg)
Example of Personality/Needs/Value/Behavior
Real-World Experiments: TravelersLikeMe

- Many people discuss travel on Twitter, some ask for advice on upcoming trips.
- We created a website (travelerslikeme.org) and twitter account (TravelersLikeMe) describing a service which makes personalized travel recommendations based on people just like you.
Mechanical Turk Study

- Majority of travel discussions on Twitter are to NYC.

- We created three messages describing TravelersLikeMe, each describing different activities:
  - Fun Message: *Coming to NYC? Follow us for personalized tips on fun bars, broadway shows, and even free kayaking*
  - Fine Lifestyle Message: *Coming to NYC? Follow us for personalized tips on luxury hotels, fine dining haunts & designer shops*
  - Social Message: *Coming to NYC? Follow us for personalized tips on social hotspots, cozy neighborhoods & themed tours*

- We asked 500 people on Mechanical Turk to evaluate these messages, and take a test for Personality, Values, and Needs.
Mechanical Turk Study - Results

- Individuals’ measured traits were significantly correlated with their preferences for each message.

- Many traits correlated, message resonance likely determined by a combination of traits.
Twitter Study

- Using Twitter streaming search & IBM Big Insights filtering, we found 4000+ travelers to NYC.

- We computed their personal traits, sent each a tweet with one of the 3 messages (randomly chosen), and measured response rates.

  - ‘Booked my trip to @Overviewproject summit in NYC. 5 days of peace, love, and documents.”
  - “Have to make a last second business trip to NY.”
  - “Heading to NYC”

List of NYC-bound travelers

Trait Profiles

Coming to NYC? Follow us for personalized tips on fun bars, broadway shows, and even free kayaking: http://bit.ly/1ap1ub6

- thanks for the tip!
- “Thanks for sharing with me. I will check it out.”
- “I live there lol”
Responses on Twitter

- Many ways for people to respond on Twitter:
  - Clicking link in tweet: expresses immediate interest
  - Retweet, Favorite, Reply our tweet: expresses engagement with or approval of our message.
  - Following our account: expresses interest in seeing messages from us going forward. Problematic, though, since some people followed us because we followed them.

- We analyzed both click rate (overall 7.23%), and retweet/favorite/reply (RFR) rate (overall 3.88%).

- RFR rates followed the preferences from the Mturk study, but not all comparisons were significant.
Twitter Study Personality/Message Results

- Performed logistic regression to understand relationship between traits and click-rates.

- Inferred personal traits *did* predict click-rates, some consistent w/Mturk study:
  - Extraversion -> social msg
  - Idealism -> finer lifestyle msg

- Low response rates make other conclusions difficult, more data being collected to better establish other correlations.
Personal Trait Study Conclusions

• Personal traits do impact preference for recommendation messages in lab study.

• Personal traits, inferred from social media, also can predict real-world responses to recommendations made via Twitter.

• It is possible to measure these effects interacting with real people in a real-world setting.
Deriving Trust

• **Trustingness**: How likely an actor is to trust another actor in the network.
  - A highly trusting actor trusts a lot of non-trustworthy actors
  - Higher score = Higher trustingness

• **Trustworthyness**: How likely an actor is to be trusted by others in the network.
  - A highly trustworthy actor is trusted by lots of non-trusting actors
  - Higher score = Higher trustworthyness

• 2 measures are negatively co-related to one another and are dependent on one another
  - Based on Hubs and Authority model from HITS algorithm
  - Twitter is a social media platform where people can verify/know identities of real persons leading to high trustworthy scores
Influence Analysis using Information Flows in Twitter Social Media

Information Flows can concisely present the frequent information flow paths of the network.

Properties satisfied:
1. Causality
2. Frequency and
3. Lifetime

Frequent Flow Path

Leader  
Follower 1  
Follower 2

\[ \text{Influence}(\text{user}) = \text{Total attention received by user as leader across all discovered flows.} \]

Our distributed influence analysis framework: Mos

Tie strength Network
Inferring Cognitive Traits: Human Dynamics

– Contextual Behavior
– Emotional State
Computational Modeling of Contextual Behavior

**Objective:** Modeling user dynamic behavior for prediction/detection tasks

**Task Goals:**
- Modeling synchronous behavior at multiple granularities
  - Predict values (e.g., performance, credibility) of entities in heterogeneous networks
  - Published at SDM 2013
- Modeling user dynamic information spreading behavior (ongoing, in demo)

**The Work:**
- Exploit the structure of people’s dynamic behaviors to facilitate prediction tasks, while few existing approaches consider that
Synchronicity Networks

• Entity synchronicity measure [Savvedra 2011]
  - E.g., how much a person’s topic sync with other people
  - No predictive power for our data

\[ s_{ikt} = T_{ikt} - T_{ikt}^{*} \]

Remove the effect of average sync

• Multi-level synchronicity networks
  - Idea: (potential) high performers *selectively* sync with others to optimally use their limited time
  - Edge weight in the same level: pairwise synchronicity

\[ e_{ij}^{(2)} = \sum_{i \in I, j \in J} (e_{ij}^{(1)}) \]

\[ e_{ij}^{(1)} = \sum_{t} o_{it} \cdot o_{jt} \]

\[ e_{km}^{(0)} = \sum_{t} \cos(P_{kt} \cdot P_{mt}) \]

- Cross-level edges
  - Between team and individual: “belong to” relationship
  - Between individual and topics: the strength of the topic in the person’s communication

Synchronicity Network for people: e.g. two people talking about the same topic in an email within an hour; they may not have direct communication

Static Network for people: direct communication
Experiment on Sychronicity Network

- **Dataset**
  - Enterprise: SmallBlue (3-Level Network)
    - 25 million emails/IM, performance metrics (e.g., utilization rate) for consultants
  - Social media: Twitter data from [Balasubramaniyan2010] (1-Level Network)
    - 70K tweets from 344 users
    - Users annotated with 4 categories
      - Celebrity, info sources, normal users, spammers
      - Manual annotation + Twitter metadata (verified, blocked etc)

- **Ranking metrics**
  - Precision-recall curves of high value entity classification for given thresholds
    (comparing with ground-truth ==> people: utilization rate; team: mean utilization rate; topic: revenue correlation)

- **Approaches to compare:**
  - Sync-HMR (Heterogeneous Multi-Level PageRank Ranking): the proposed approach
  - Static-HMR: apply HMR algorithm on static social networks
  - Sync-SVR (Support Vector Regression): apply SVR on synchronicity networks
    (using network diversity, sizes, strong link to mgrs.)
  - Static-SVR: apply SVR on static social networks

- All results are obtained using five-fold cross validation.
Evaluation – Is Synchronicity Network a good indicator for high value entities?

- Sync-HMR consistently outperform baselines
- Sync-SVR does not always outperform static-SVR
  - The structural features of synchronicity is important

=> Multi-Level Sychronicity Networks captures heterogeneous hidden dynamic interactions; One's performance is related to her capability to 'sync' with important people.
Baseline: [Balasubramaniyan2010]
- Interaction network is better than follower network to detect spammers and celebrities/info sources from normal people.

\[ \xi = 1 \] filter spammers

\[ \xi = 2 \] detect celebrities and info sources

\[ \Rightarrow \] Sychronicity Network is better than the Interaction Network on classifying users.
Data:
- All instant messages and trades by employees of a large hedge fund.
- 24 are traders, 95 are analysts, 63 are portfolio managers, 8646 outside contact
- 47K trades
- 22 million IMs (2008 – 2012)

Findings: We identify two behavioral patterns that signal system changes:
- Reaction to IMs containing relevant information
- In-group vs. out-group communication

Using these two features, we can make predictions of system-wide changes with better accuracy than the group’s predictions.
13:11:33, I was thinking all this AAPL anti-trust might be actionable
13:11:42, not great for AAPL
13:11:47, When GOOG had that big issue in Europe stock underperformed right?
13:11:52, true
13:14:01, Also not sure if you caught, but GSCO is going to allow employees to bring own phone device for corporate email
13:14:24, Maybe GSCO allowing that could be positive for AAPL, as security focused firm saying iPhone works
13:14:35, But bad for RIMM
13:14:42, Maybe all this is priced in
13:16:50, Did you see speculation that Bing is actually quietly going to be default search on iPhone 4?
13:17:18, heard a lot of talk of that
13:17:23, but didn't see that specifically like that
13:17:44, Okay let me figure out where I saw that and get back to you
13:17:45, One sec
• **Motivation**
  Emotional states can affect how information is processed. Good information can be undermined or strengthened by emotional states.

• **Approach**
  – Measure emotional activation in tweets using the ANEW dictionary
  – Control for the number of words in the text

• **Preliminary experiments**
  – Traders at a hedge fund are more likely to make decision errors when they are very emotionally activated or very emotionally deactivated.
  – Users who retweeted the 20 detected most anomalous sequences tend to post tweets with higher level of emotion than a baseline of 20 million tweets from June 2009.
Inferring Cognitive Traits: Human Dynamics

– Information Reasoning & Morphing
– Visual Sentiment
Information Morphing Modeling

- **Objective:** Modeling to detect and track information evolution in social media

- **Task Goals:**
  - Resolve information morph, where new links keep emerging to give new meaning to existing phrases
    - Published at ACL 2013
  - Detect information morph
    - Ongoing

- **The Work:**
  - Exploit rich structure information in heterogeneous information networks to improve existing NLP based methods

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**Peace West King** from Chongqing fell from power, still need to *sing red songs*?

**Bo Xilai** led Chongqing city leaders and 40 district and county party and government leaders to *sing red songs*.
Morph Resolution Approach Overview

Target candidate identification

• Narrow down candidate space by selecting pairs of similar temporal distribution

Surface features (NLP)

• Probabilistic Orthographic Model (e.g., string edit distances)
Similarity Features to Detect Morphing

- Heterogeneous information networks based features
  - Meta-path-based features
    - Measuring path similarity to other nodes of the Target Node and the Morphing Candidate Nodes (e.g., random walk, K-L divergence)
    - Considering NLP feature similarity and temporal correlation simultaneously of two terms

- Social networks features
  - A morph and its target are more likely mentioned by two users with strong social correlation
  - Measuring tie strength by social interactions (e.g., retweet, mention)
Social Features

• Social networks based feature
  - A morph and its target are more likely mentioned by two users with strong social correlation
  - Measuring tie strength by social interactions (e.g., retweet, mention)

• Measure semantic similarity via social features

\[ s(m, e) = \sum_{t \in T} \frac{f(e, t, U_t, U_c)}{|T|} \]

- \( T \): the set of temporal slots a morph \( m \) occurs
- \( U_t \): the set of users whose posts include \( m \)
- \( U_c \): be the set of close friends (i.e., social distance<0.5) for \( U_t \)
- \( f(e, t, U_t, U_c) \): an indicator function which returns 1 if one of the users in \( U_t \) posts tweets include the target candidate \( e \) within 7 days before \( t \)
Data and Scoring Metric

- **Data**
  - Time frame: 05/01/2012-06/30/2012
  - 1555K Chinese messages from Weibo
  - 267K formal web news documents from embedded URL
  - 500K Chinese messages from English Twitter for sensitive morphs
  - Test on 133 morph entities in Weibo

- **Scoring Metric**
  
  \[
  \text{Acc@} \ k = \frac{C_k}{T}
  \]
  
  - \(C_k\): the number of correctly resolved morphs at top position K
  - \(T\): the total number of morphs in ground truth

<table>
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<tr>
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<th>Acc@1</th>
<th>Acc@5</th>
<th>Acc@10</th>
<th>Acc@20</th>
</tr>
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<td>Weibo</td>
<td>0.234</td>
<td>0.416</td>
<td>0.477</td>
<td>0.519</td>
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<tr>
<td>All sources</td>
<td>0.379</td>
<td>0.594</td>
<td>0.659</td>
<td>0.701</td>
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</table>
Task 2.5: Multimedia Analytics (Columbia University)

- **Objective**: Detect and track opinion-influencing visual memes

- **Task Goals**:
  - Goal 1 & concrete achievements
    - Since Feb 2012: Visual Sentiment Ontology (VSO) & SentiBank classifiers
    - Since Feb 2013: Release dataset, browsers, 1200 classifiers, and twitter sentiment prediction demo
    - By Jan 2015: Adaptive analysis for specific user groups and data domain
  - Goal 2
    - Enhance communication and story telling using multimedia content

- **The Work**:
  - Achieves the first multimedia-based sentiment prediction system
  - Facilitates trend tracking and informed decision making based on multimedia

- **New Publications, Awards**:
  - [ACMMM2013 BNI Paper and Demo]: Large-scale Visual Sentiment Ontology and Detectors Using Adjective Noun Pairs

- **Tech transition strategy**:
  - Adapt SentiBank classifiers and VSO browser to analyst target content
The Power of Social (Visual) Multimedia
- A picture is worth one thousand words

Tweets of the Year

@BarackObama: Four more years.  
@Brynn4NY: Rollercoaster at sea.
Question: How to Build Visual Sentiment Ontology?

-- Web + big data + computer vision + psychology

Psychology emotion wheel
(24 emotions, by Robert Plutchik)

Plenty on the Web:
“For content to go viral, it needs to be emotional,” Dan Jones
Research: Which 1000 sentimental concepts?
-- data mining to discover visual sentiments in social media

Psychology emotion wheel (24 emotions)

Build Sentiment Ontology

Select Adj-Noun Pairs

Analyze tags with strong sentiments

MISTY WOODS

SAD EYES
Concurrent tags with emotions

<table>
<thead>
<tr>
<th>joy</th>
<th>terror</th>
<th>amazement</th>
<th>disgust</th>
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<td>joy</td>
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<tr>
<td>christmas</td>
<td>bomb</td>
<td>landscape</td>
<td>insect</td>
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</table>

From 6 million tags on Flickr and YouTube
Color code: text sentiment values
Target Concepts for CV - Adj-Noun Pair

Adjective (268): indicate strong emotions
  frequent positive Adj: beautiful, amazing, cute
  frequent negative Adj: sad, angry, dark

Nouns (1187): more detectable by computer vision
  Noun categories: people, places, animals, food, objects, weather

Other cleaning steps:
  remove named entities like “hot dog” via wikipedia
  Choose sentiment rich ANP concepts by tools
    “Senti-WordNet” “SentiStrength”
Beautiful Sky

Beautiful Flower
Sad Eyes

Happy Face
Image Datasets

About 0.5 million images over 3000 concepts

- # images on Flickr per ANP
- # CC images downloaded from Flickr per ANP
Next Step:
Teach Machine to Recognize Visual Sentiments

Psychology emotion wheel (24 emotions)

Build Sentiment Ontology

Select Adj-Noun Pairs

Train Classifiers

Performance Filtering

SentiBank (1200 Detectors)

Sentiment Prediction

S.F. Chang
Classifier Training

- LibSVM, cross validation
  - Generic features
  - Color Histogram (3x256 dim.)
  - GIST descriptor (512 dim.)
  - Local Binary Pattern (52 dim.)
  - SIFT Bag-of-Words (1,000 codewords
    - 2-layer spatial pyramid, max pooling)
  - Classemes descriptor (2,659 dim.)

- Special features
  - Object detection (people, objects, etc.)
  - Aesthetics features (color schemes, layout, etc.)
  - Face and attributes
  - Improve accuracy 9%-30%
Examples

Good Results:

(a) colorful clouds

(b) misty night

Not Great Results:

(c) colorful butterfly

(d) crying baby
Sentiment Prediction Performance

Sentiment Prediction Accuracy

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<td>(many are neutral)</td>
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<td>Text</td>
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Examples

- Text:
  - young_teen happy_heart young_friends fat_girls happy_face
cute_girls fluffy_cat sweet_girls cute_dog friendly_smile
funny_kids

- Visual:
  - young_friends cold_feet stupid_hat heavy_winter
waiting_area crazy_hair stupid_sign fat_face harsh_winter

- Text-Visual (Joint):
  - happy_heart sweet_girls friendly_smile traditional_wedding
grumpy_face young_teen handsome_face beautiful_flower
wedding_friends happy_wedding

- Text-Visual (Joint):
  - violent_crime bad_guy dark_blood clean_air
ancient_sculpture funny_comic angry_men gorgeous_girls
tired_eyes tired_men dark_death dark_eyes traditional_tattoo

- Text-Visual (Joint):
  - sweet_child great_night tired_eyes creepy_horror
dark_places dark_blood dark_woods wet_window dark_room
favorite_book young_friends dark_death weird_face
hardcore_band favorite_club hardcore_punk
SMISC Demo

– Live Monitoring:
  – Retweets, Visualization, Translation, Sentiments
  – Relationships, Communities
  – Geo-Location, Intranet Social Media

– Forensic Anomaly Detection:
  – Abnormal Threads
  – Personality, Value, Needs, Trustworthiness, Emotions,..
  – Visual Sentiments
SMISC Forensic System

Updating User Behavioral Model

- Data Ingest & prep.
- Social Tie Strength Estimation
- User Behavior Statistics

Social Media Data Store

User Behavioral Models

Social Network Models

Graph Analytics

Emotion Analytics
- Egonet Analytics
- Graph Similarity (Rutgers)
- Influence/Trust (UMN)
- Human Personality & Value
- Emotion Activation (UNW)

Detecting Anomalous Sequences that may be disinformation

RT sequence extraction & filtering (keyword, loc etc)

Multimedia Sentiment Tracking

Top K Sequences

Visualization

*Note: Components in blue are work in progress and applied to the top-K sequences*
• Motivation
  – People’s dynamic reactions to information (e.g., retweeting) give clues to information credibility and quality
    • For example, trustworthy people may take time to verify uncertain information from strangers before spreading it

• Approach
  – Use one-class conditional random field to model people’s behavior in information spreading sequences and detect anomalous sequences
    • Features: content features such as emotion, network features such as tie strengths and clustering coefficients

• Preliminary experiments
  – Detect anomalies in retweeting sequences during Hurricane Sandy
    • Including hijacker, fake pictures spreaders

One-class CRF to detect temporal anomalies

Detected as top 1 anomaly in Sandy Tweets
Photo Tweet Sentiment Tracking during Hurricane Sandy (Columbia University)

- **Goal:** Detect sentiment during Hurricane Sandy.

- **Data collection:**
  - Date: Oct 25 – Nov 02
  - Hashtags (based on popularity): #prayforusa, #frankenstorm, #nyc,#hurricane,#sandy,#hurricanesandy, #staysafe, #redcross,#myheartgoesouttoyou,…
  - 2000 Photo Tweets collected

- **Ground Truth Labeling:**
  - 1340 unanimously agreed labels from 2 individuals

- **Training Classifier:**
  - Text (SentiStrength)
  - Visual(SentiBank, Logistic Regr.)
  - Training/Testing ratio: 4:1
  - 5-fold cross-validation
  - Accuracy(Text-Visual Combined): 72%
Detect disinformation spreading (retweet) during Hurricane Sandy by people’s dynamic behavior in response to the information

Detected rumor: Shark in NJ

User info (e.g., personality chart)

The rumor sequence has low trustworthiness users involved

Human personality, value traits to show (showing Trustworthiness)
Users can interactively analyze the personality traits, emotion activation, value and other traits of the people involved.
Evaluation with Hurricane Sandy Data

- Goal: detect disinformation spreading during Hurricane Sandy 2012
- Dataset: 10% Twitter feed on Oct 29, 2012 when Hurricane Sandy hit NYC
- Ground truth: annotation based on verified disinformation revealed by credible sources afterwards
  - E.g., http://mashable.com/2012/10/29/fake-hurricane-sandy-photos/
- Metric: accuracy of detected disinformation in top-K results
  - Baseline: One-Class SVM using the same set of features

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```
Evaluation with Boston Bombing Data

- Goal: detect disinformation spreading during Boston Bombing 2013
- Dataset: 10% Twitter feed during Apr 15-19, 2013
- Ground truth: annotation based on verified disinformation revealed by credible sources afterwards
  - E.g., http://www.snopes.com/politics/conspiracy/boston.asp
- Metric: accuracy of detected disinformation in top-K results
  - Baseline: One-Class SVM using the same set of features

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Homework #2

Based on the systems implemented in Homework #1 to implement a stock prediction system. Reference the methodology introduced in Lecture 2, with any additional method/tool.algorithm/data of your choice.

The grading of Homework #2 will depend on the prediction accuracy — the date after your submission.

TA will announce a list of companies to be predicted and the way to submit your result.

You can use any tool.