

Mining user activity data in social media services

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PhD Thesis Defense, ICMC – USP, May 2017



Outline

1. Introduction
2. Contribution 1: the Act-M Model
3. Contribution 2: the VnC Model
4. Contribution 3: the MFS-Map Method
5. Conclusions

Introduction

Social media services have a growing impact in our society:

- Highly popular: over 47% of Brazilians are social media users
- News consumption: less TV, more social media feeds
- Targeted advertisement

Social media services generate and store a large volume of data on how user behave

- Large number of potential applications (e.g. design of highly accurate fraud detection methods)

Introduction

Research goal: How can we extract useful knowledge from social media data?

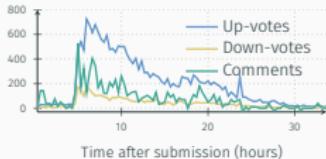
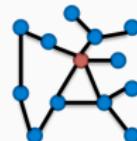
Challenges: social media data is...

1. **Complex:** objects are represented by a large number of attributes
2. **Diverse:** can be represented by images, time-series, graphs, textual information



Feature Vector

$\{v_1, v_2, \dots, v_n\}$



Thesis

Data from social media services obey patterns that can be explored to design specialized methods for mining the raw data and improve the accuracy of prediction, anomaly detection and forecasting tasks when compared to traditional non-specialized data mining methods.

Research problems:

1. Temporal analysis users' actions
 - What patterns can be discovered from the time-stamps of users' activities?
 - Is it possible to use this data to detect anomalous behavior?
2. Modeling how the volume of users' interactions evolves over time
 - If a picture receive 2,000 “likes”, how many comments is it expected to receive?
3. Automatically annotating social media images
 - Can we search for social images even when textual metadata is missing?

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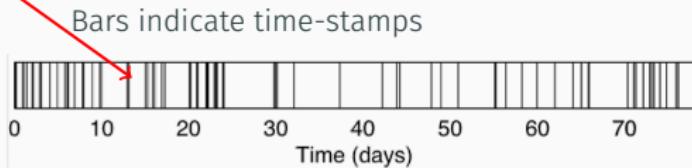
Act-M Model: Problem Statement

Users generate sequences of time-stamps when they use a social media Web site:

ACM SIGKDD KDD'15 @kdd_news · Jul 3
Kdd Sydney August- Early Bird registration deadline extended to July 7th, 2015. kdd.org/kdd2015/regist...

2:16 PM - 3 Jul 2015 · Details

Sequence of tweets
time-stamps:



What can we learn from time-stamps?

- Are there common patterns?
- Can we tell if a user is a bot or a human?

Act-M Model: Pattern Mining – Datasets



Reddit



Twitter

- 21,198 users

- 6,790 users



Stack-Overflow

- 8,755 users

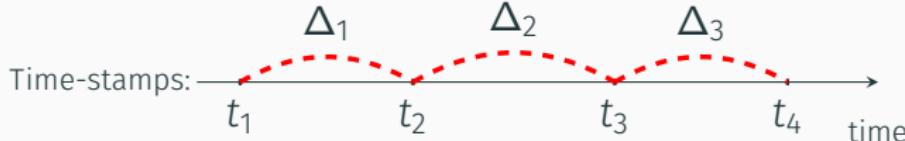


Hacker-News

- 1,368 users

For each user we have:

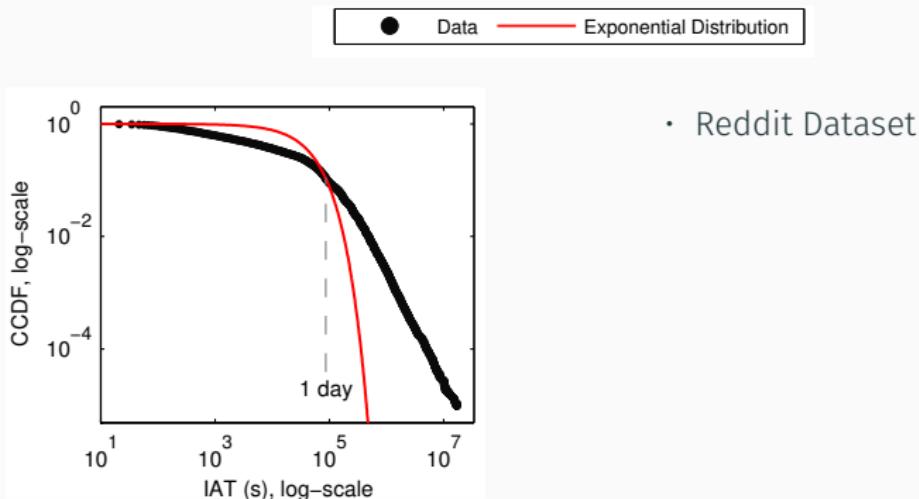
- Sequence of postings time-stamps: $T = (t_1, t_2, t_3, \dots)$
- Inter-arrival times (IAT) of postings: $\Delta = (\Delta_1, \Delta_2, \Delta_3, \dots)$



Pattern 1: The distribution of IAT is heavy-tailed

Users can be inactive for long periods of time before making new postings

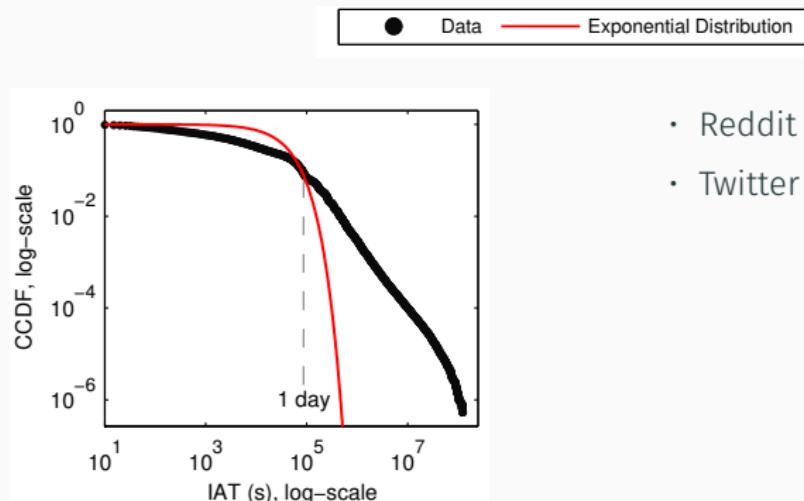
IAT Complementary Cumulative Distribution Function (CCDF) (log-log axis)



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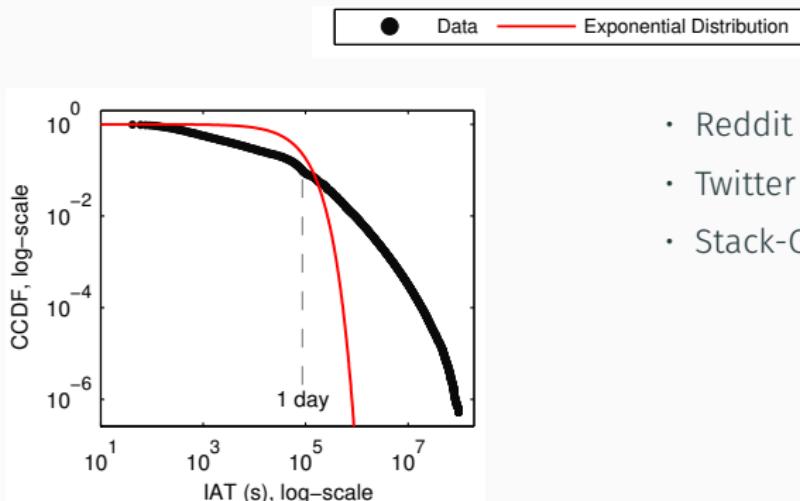


- Reddit Dataset
- Twitter Dataset

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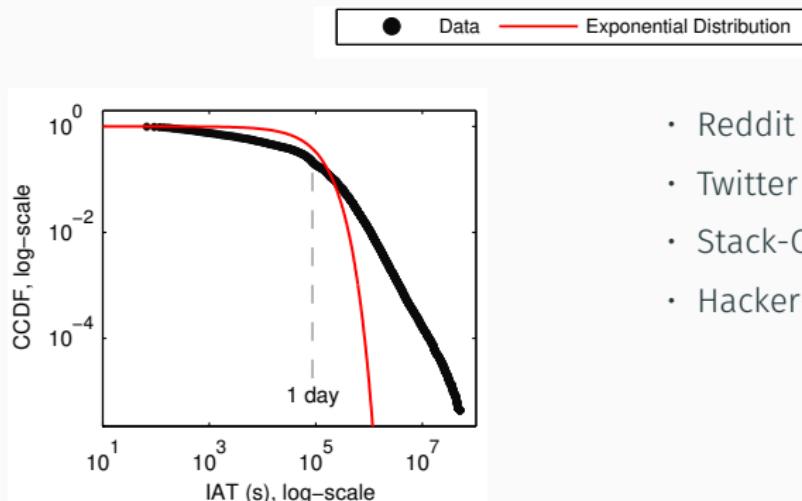


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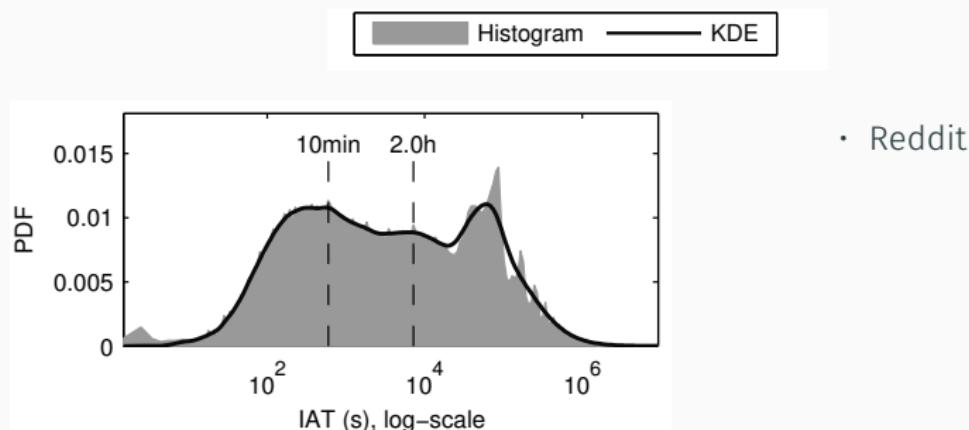


- Reddit Dataset
- Twitter Dataset
- Stack-Overflow Dataset
- Hacker-News Dataset

Pattern 2: Bimodal IAT distribution

Users have highly active sessions and resting periods

Log-binned histogram and KDE of postings' IAT



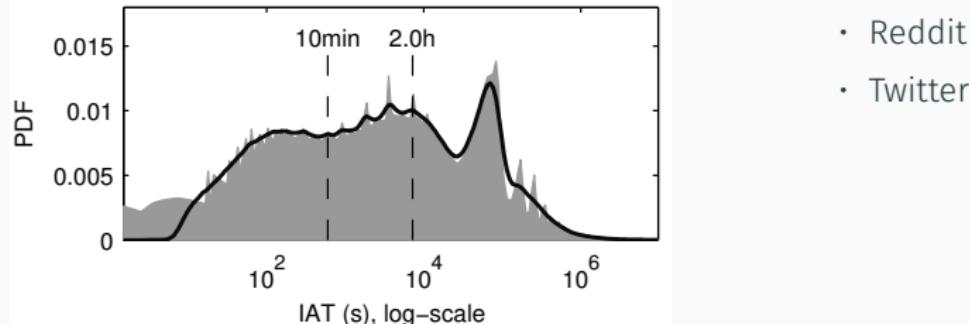
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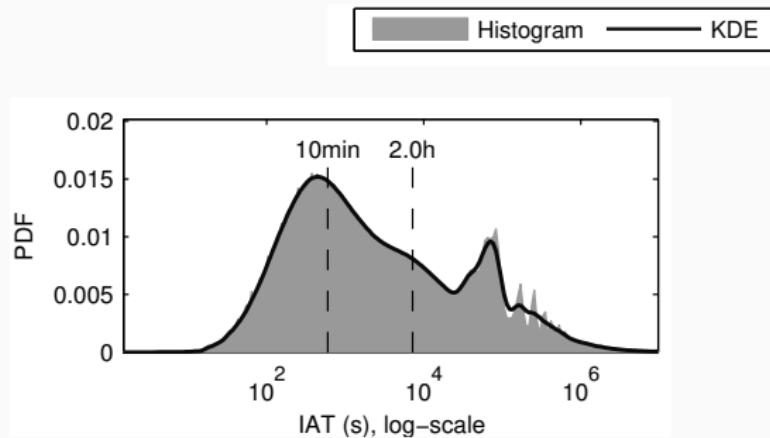
Histogram —— KDE



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Log-binned histogram and KDE of postings' IAT

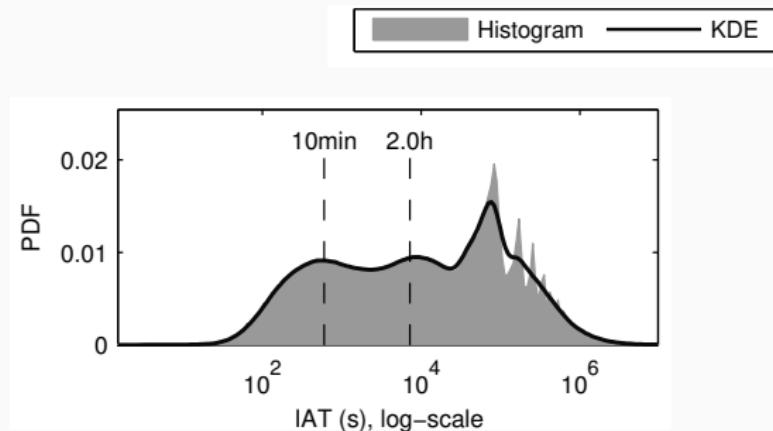


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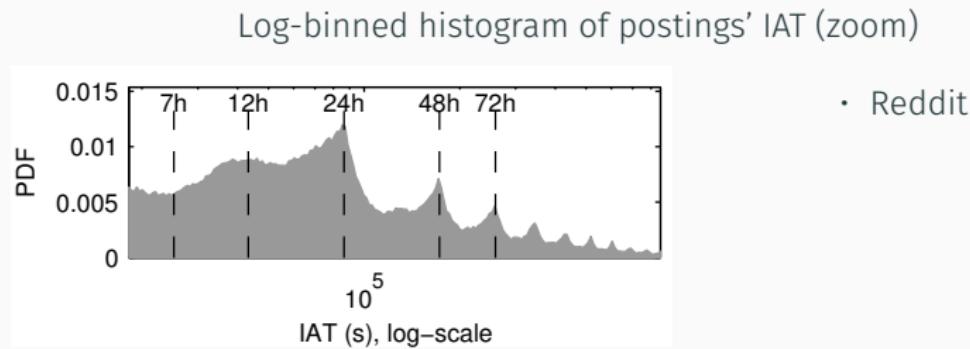
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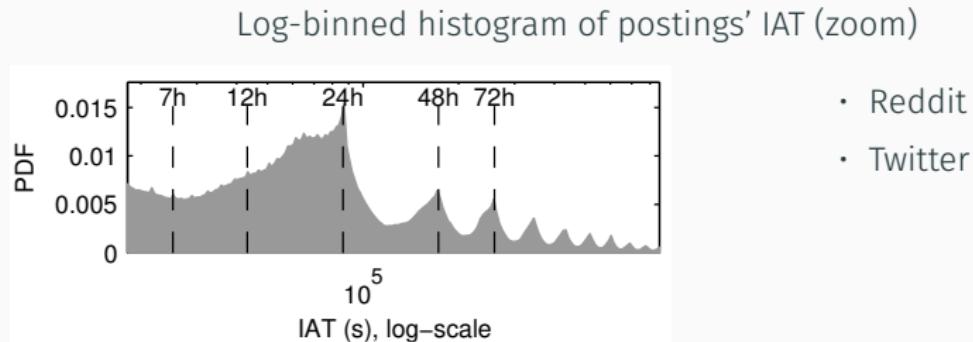
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Users' daily sleeping intervals create periodic peaks in the log-binned histogram of IAT



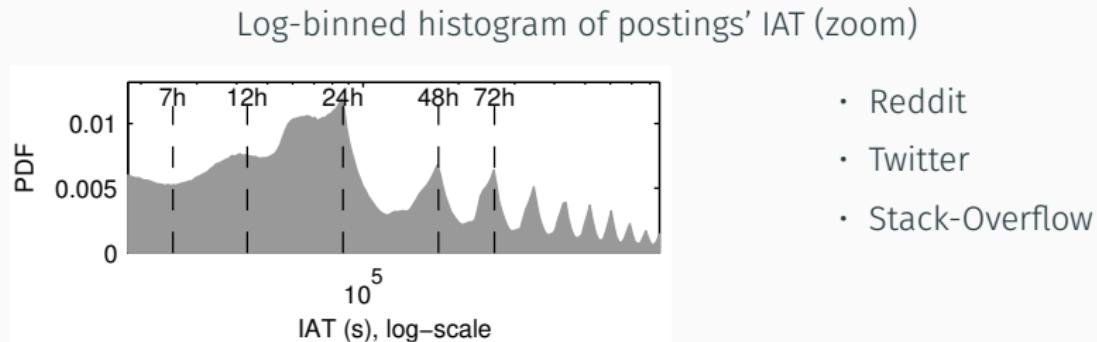
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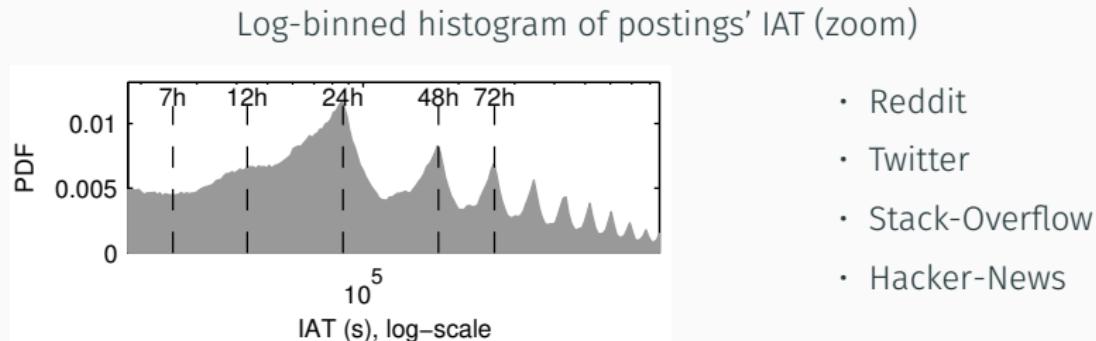
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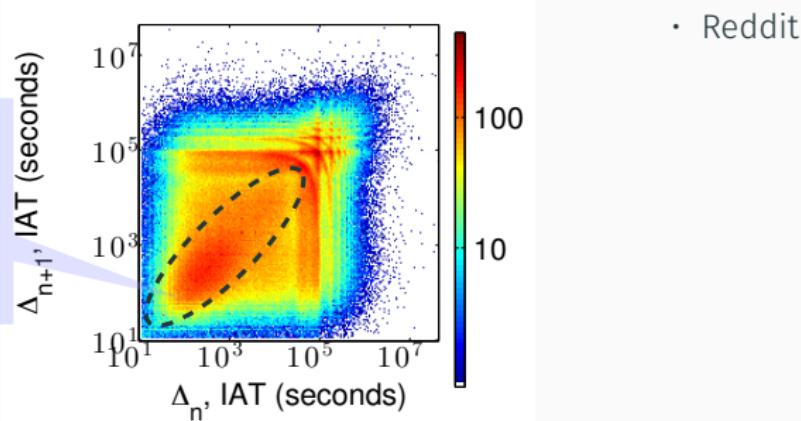


Pattern 4: Consecutive IAT are correlated

Long/short IAT are likely to be followed by long/short IAT

Joint distribution of consecutive IAT (heat-map)

Concentration
of pairs in the
diagonal: posi-
tive correlation

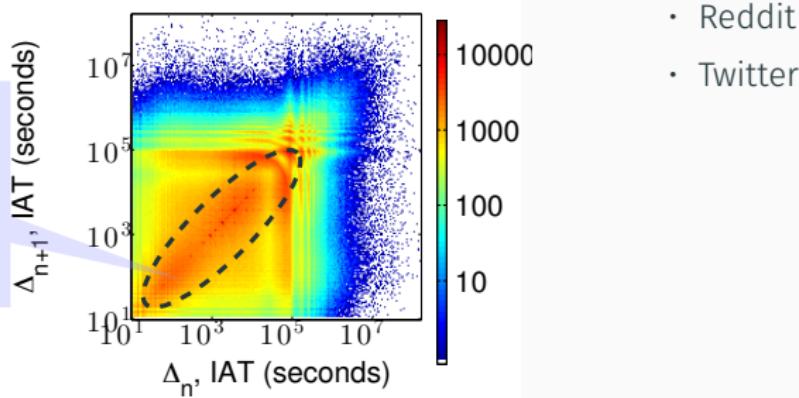


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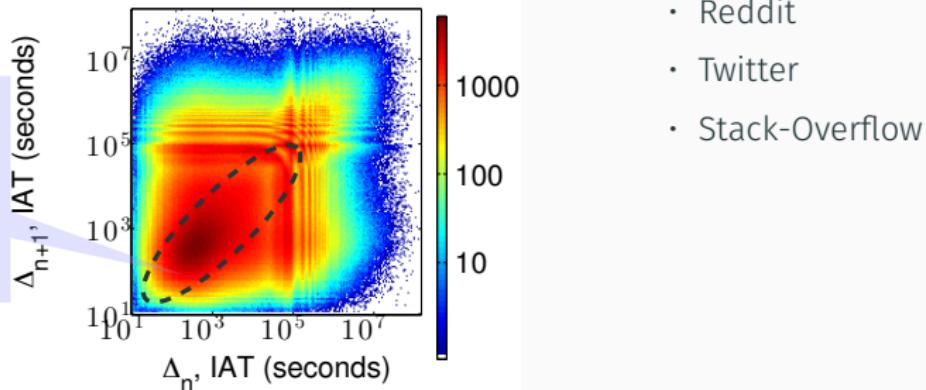


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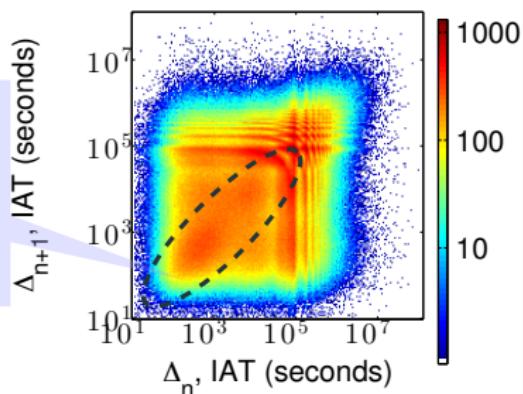


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- Reddit
- Twitter
- Stack-Overflow
- Hacker-News

Act-M (Activity Model)

Can we generate synthetic time-stamps that match real data patterns?

Pattern	Poisson	Power-Law Barabási, 2005	CNPP Malmgren, 2009	SFP Vaz de Melo, 2013	Act-M Proposed
Heavy Tails		✓		✓	✓
Bimodality			✓		✓
Periodic Spikes					✓
IAT Correlation				✓	✓

Goal

Design a model that matches all the activity patterns.

Act-M Model: SCorr Process



Base model: Self-Correlated Process (SCorr) process

- **Definition:** A stochastic process is a SCorr process with base rate λ_o and correlation ρ if:

$$\delta_1 \sim \text{Exp}\left(\frac{1}{\lambda_o}\right), \delta_i \sim \text{Exp}\left(\rho \cdot \delta_{i-1} + \frac{1}{\lambda_o}\right)$$

$X \sim \text{Exp}(1/\lambda)$: Exponential random variable with rate λ

Properties:

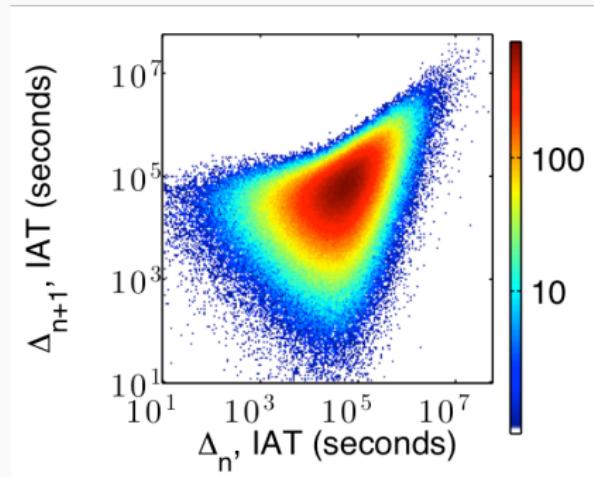
- **Correlated IAT:** The i -th IAT δ_i depends on the previous IAT δ_{i-1}
- **Correlation Strength:** ρ controls correlation strength. If $\rho = 0$, SCorr reduces to an exponential distribution

Act-M Model: SCorr Process

Act-M Model:



Consecutive IAT Distribution



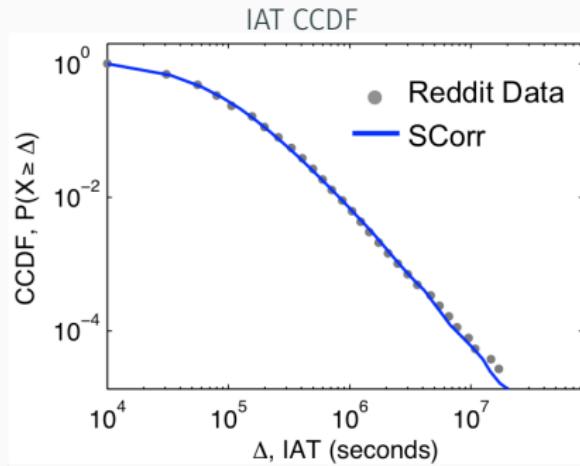
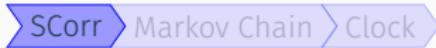
Patterns:

- Correlated IAT

$$\lambda = 20\text{h}, \rho = 0.7$$

Act-M Model: SCorr Process

Act-M Model:



$$\lambda = 20\text{h}, \rho = 0.7$$

Patterns:

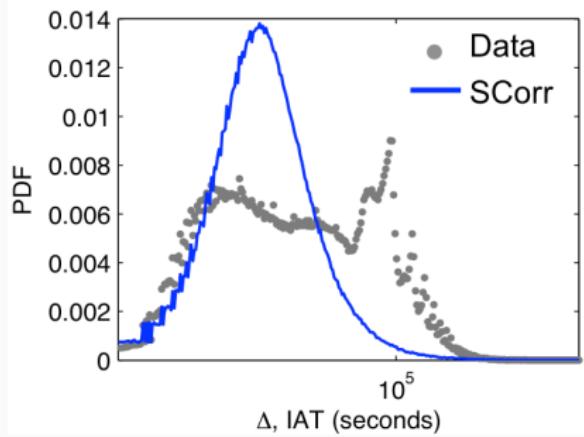
- Correlated IAT
- Heavy-tail

Act-M Model: SCorr Process

Act-M Model:



IAT Log-binned Histogram



$$\lambda = 20\text{min}, \rho = 1.0$$

Patterns:

- Correlated IAT
- Heavy-tail
- Bimodality
- Periodic Spikes

Act-M Model: Markov Chain

Act-M Model:



Active State:

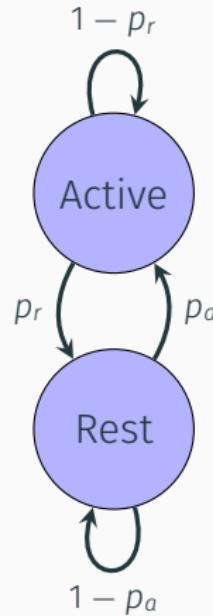
1. Wait $\delta_i \sim \text{SCorr}(\lambda_A, \rho_A)$
2. Make a post
3. Transition

Rest State:

1. Wait $\delta_i \sim \text{SCorr}(\lambda_R, \rho_R)$
2. Transition

Base Rates $\lambda_A > \lambda_R$

- Active state avg. wait time is smaller than rest state avg. wait time

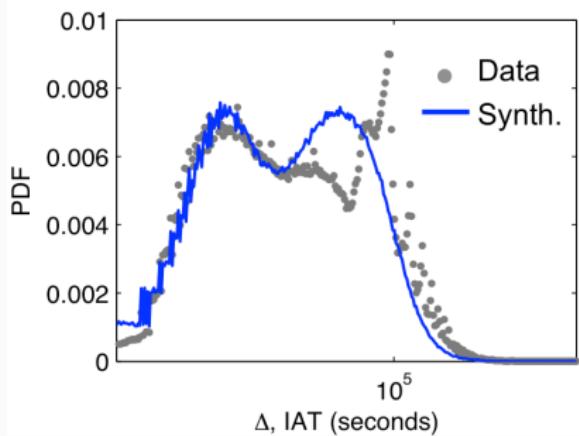


Act-M Model: Markov Chain

Act-M Model:



IAT Log-binned Histogram



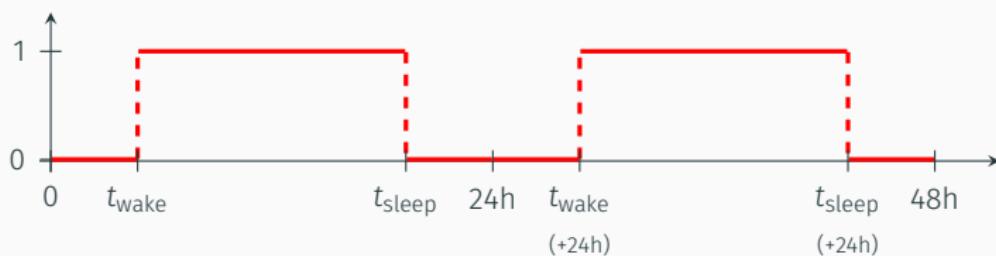
Patterns:

- Correlated IAT
- Heavy-tail
- Bimodality
- Periodic Spikes

Act-M Model: Clock

Act-M Model: SCorr → Markov Chain → Clock

Probability p_a of becoming active changes over time:



Clock variable t_{clock} keeps track of current time:

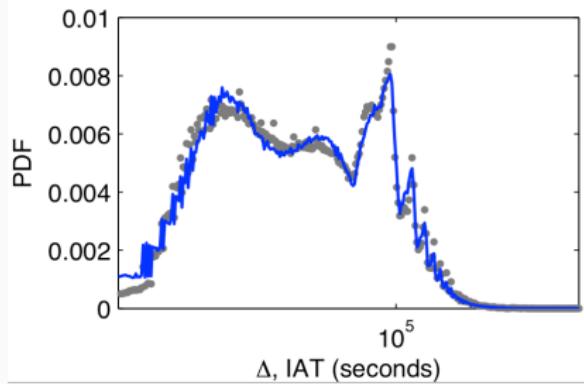
- $0:00:00h < t_{\text{clock}} < 23:59:59h$
- Update t_{clock} after each state transition

Act-M Model: Complete

Act-M Model:



IAT Log-binned Histogram



Patterns:

- Correlated IAT
- Heavy-tail
- Bimodality
- Periodic Spikes

Parameter Estimation

We use the Levenberg-Marquardt algorithm to minimize the difference between the Act-M and the data histograms.

Act-M Model: Experiments – Can It Match Real Data?

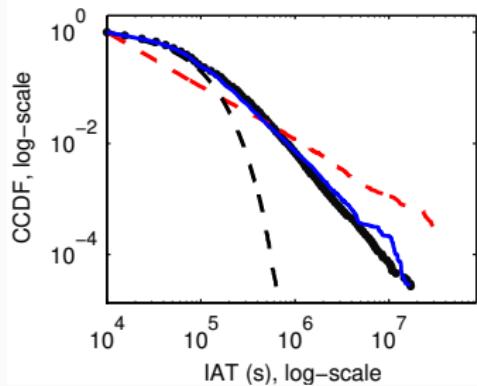
CNPP
Malmgren et. al

SFP
Vaz de Melo et. al

Act-M
Proposed Model

● Data — ActM - - CNPP - - SFP

IAT CCDF



Pattern	CNPP	SFP	Act-M
Heavy-Tail	No	Yes	Yes
Bimodality			
Spikes			
Correlation			

Act-M Model: Experiments – Can It Match Real Data?

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Act-M
Proposed Model



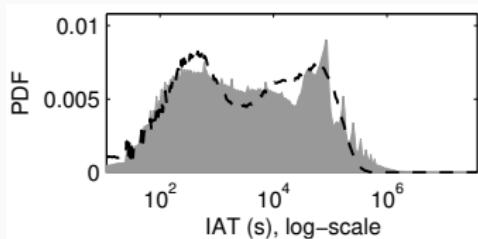
Data

ActM

CNPP

SFP

IAT Log-binned Histogram



Pattern	CNPP	SFP	Act-M
Heavy-Tail	No	Yes	Yes
Bimodality	Yes		
Spikes	No		
Correlation			

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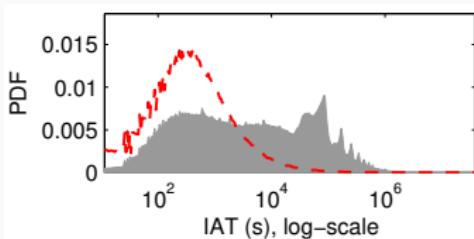
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Pattern	CNPP	SFP	Act-M
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Correlation			

Act-M Model: Experiments – Can It Match Real Data?

CNPP

SFP

Act-M

Proposed Model

1

Data

- ActM

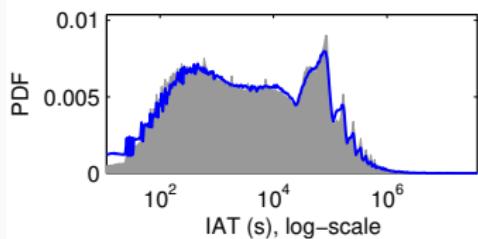
— — — CNPP

-

- SF

1

IAT Log-binned Histogram



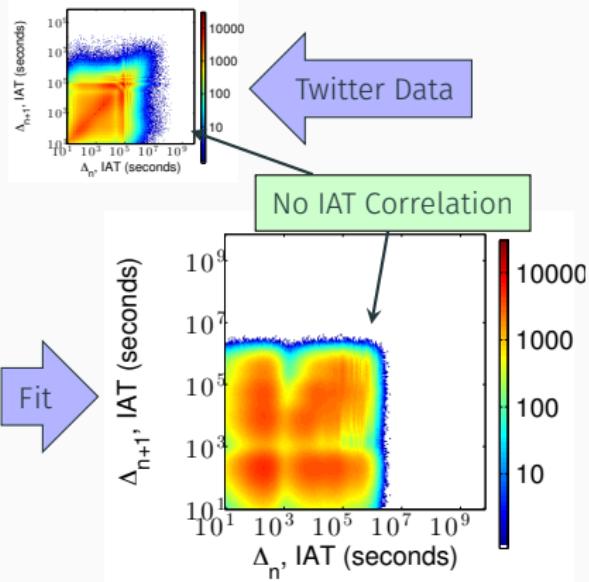
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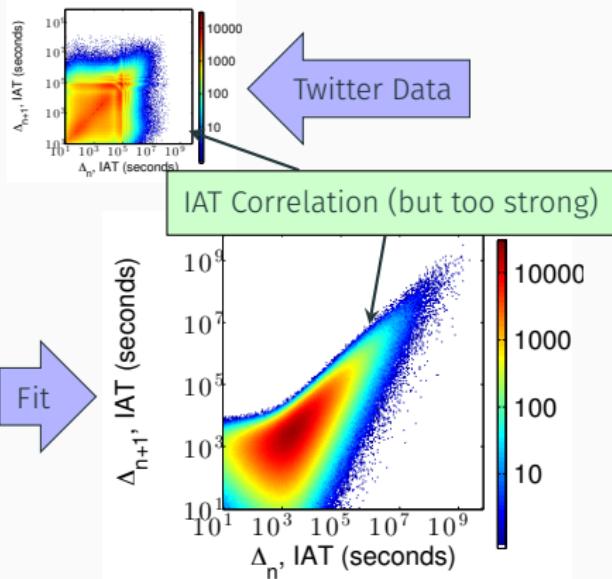
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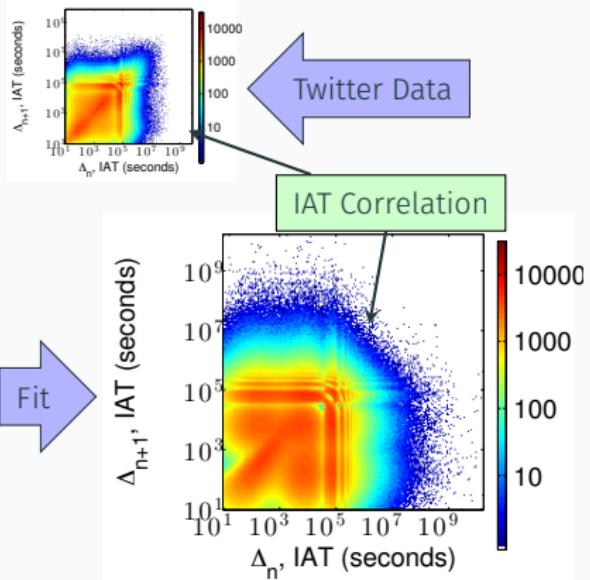
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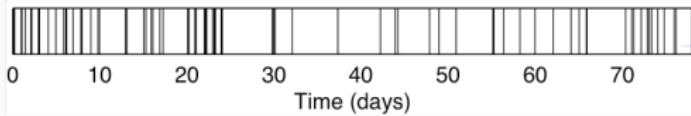
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Correlation	No	Yes	Yes

Act-M Model: Bot Detection

Problem: Bot Detection

Given labeled time-stamp data from a set of users $\{\mathcal{U}_1, \mathcal{U}_2, \dots\}$ decide if an unknown user \mathcal{U}_i is a human or a bot.

Time-stamps from a single user



The user that produced
the time-stamps is
a human or a bot?

Solution: ActM-Spotter

- Compare users' IAT to synthetic IAT generated by the Act-M
- If not similar to Act-M, then the user is likely to be a bot

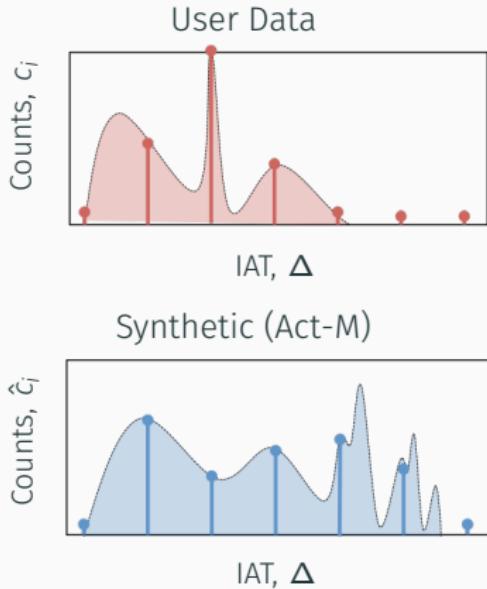
Act-M Model: Bot Detection

Training: estimate Act-M parameters

- Using time-stamps from all users from a dataset

For each user:

1. Compute the IAT histogram
2. Generate synthetic time-stamps using Act-M
 - Same number of time-stamps as the user
3. Compare user and synthetic IAT histogram
 - Cost-sensitive classification using the dissimilarity



$$\text{Dissimilarity} = \sum_{j=1}^K |c_j - \hat{c}_j|$$

Act-M Model: Bot Detection – Experiments

Datasets: users were manually labeled as bots or humans

1. **Reddit:** 1,963 humans / 37 bots
2. **Twitter:** 1,353 humans / 64 bots

Baseline methods:

1. **IAT Histogram:** log-binned IAT histogram
2. **Entropy (Chu et al.):** entropy of the IAT distribution

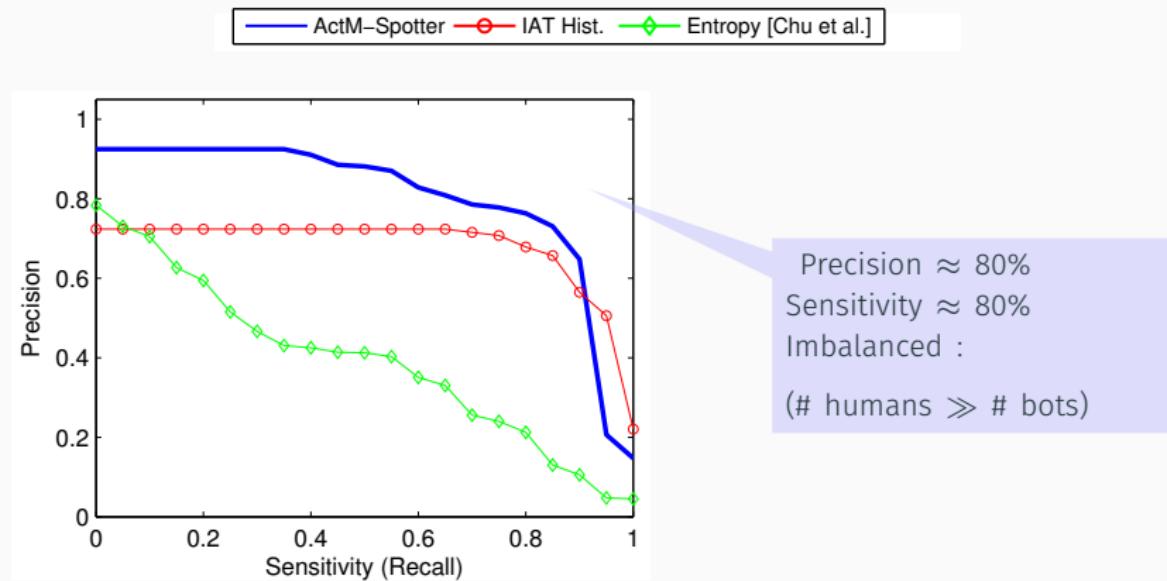
Training:

- Same size for train and test subsets (preserved class distribution)

Act-M Model: Bot Detection – Experiments

Precision vs. Sensitivity Curves

- Good performance: curve close to the top of the plot

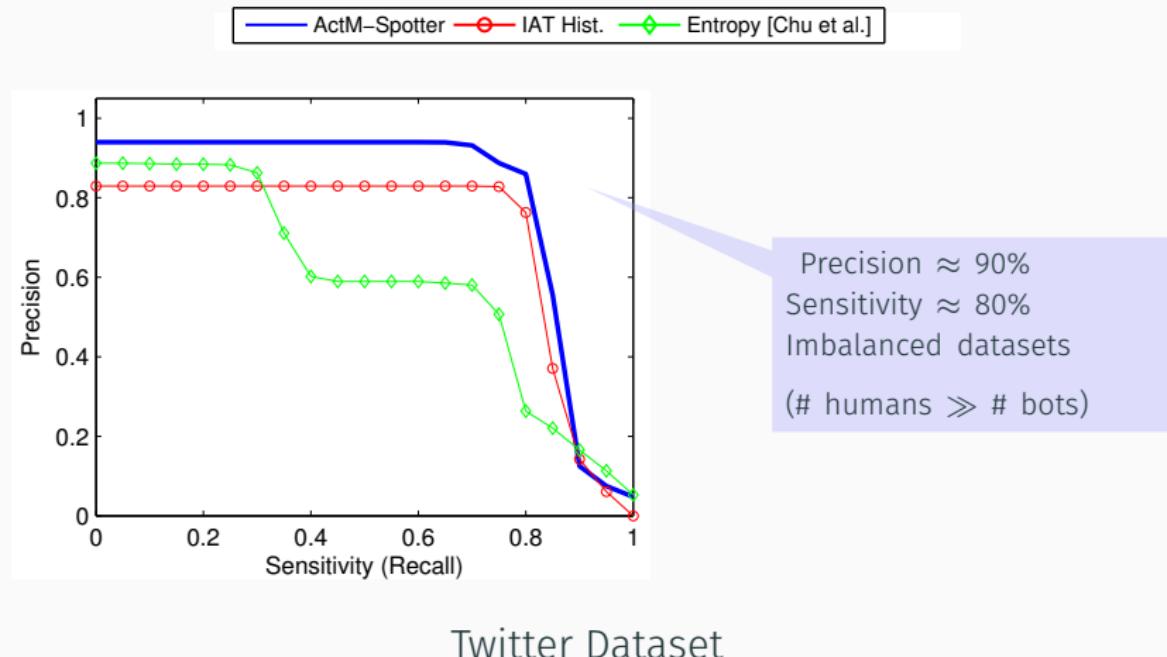


Reddit Dataset

Act-M Model: Bot Detection – Experiments

Precision vs. Sensitivity Curves

- Good performance: curve close to the top of the plot



Act-M Model: Summary

Pattern Mining:

- We showed that the IAT distribution of users' postings in social media is characterized by four patterns: heavy-tails, bimodality, periodic spikes and positive correlation

The Act-M Model:

- Mathematical model that matches the IAT distribution of social media users' postings

Bot Detection:

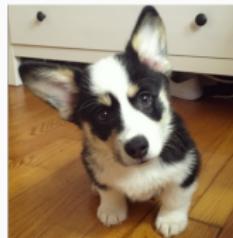
- We can use the Act-M to tell if a user is a bot based only on time-stamp data

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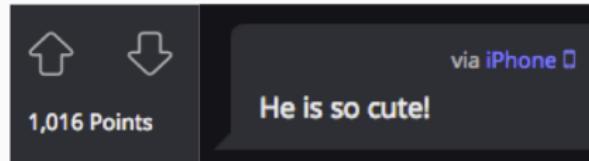
VnC Model: Introduction

In **social voting services**,
users can submit content
(e.g. pictures, news articles)



And other users can:

- Up-vote (like)
- Down-vote (dislike)
- Post comments

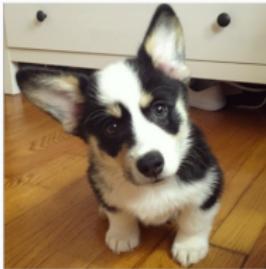


Examples of social voting services: Reddit, Imgur, Hacker-News

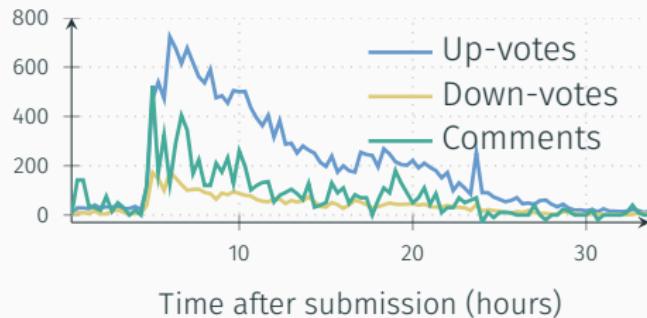
VnC Model: Problem Statement

For a submission, we have 3 time-series: up-votes $v_+(t)$, down-votes $v_-(t)$ and comments $c(t)$:

Submission



Time-Series



Problem

Can we explain how $v_+(t)$, $v_-(t)$ and $c(t)$ evolve over time?

Vote-and-Comment (VnC) Model

VnC: mathematical model that describes how the volume of up-votes, down-votes and comments changes over time

VnC is composed of 3 submodels that describe the following relationships:

1. Up-votes over time
2. Up-votes vs. down-votes
3. Comments vs. votes

VnC Model: Up-votes Over Time

The number $v_+(t)$ of up-votes received by a submission at time t is a function of:

1. $P(t)$: probability of a user up-voting at time t
2. N_+ : population of potential voters
3. $V_+(t)$: number of votes *accumulated* at time t

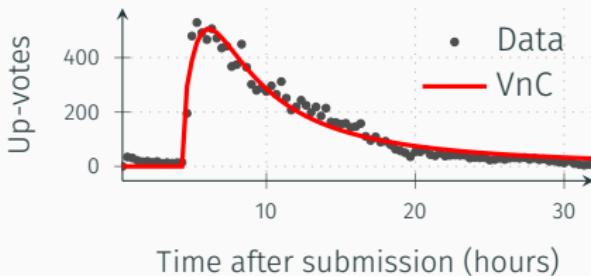
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Up-votes over Time

$$v_+(t+1) = \underbrace{[N_+ - V_+(t)]}_{\text{users that can vote}} \cdot P(t)$$

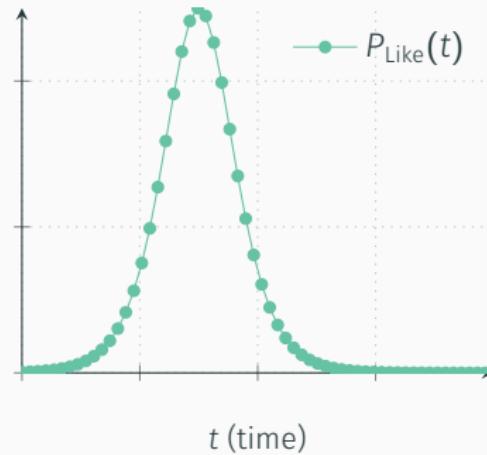


Next Step: How can we model the probability $P(t)$?

VnC Model: Up-voting Probability

$P_{\text{Like}}(t; \beta_+, \xi_+)$: Probability of liking a submission

- Cascading Mechanism:
popularity affects probability
- $P_{\text{Like}}(t) = \xi_+ + \beta_+ \cdot V_+(t)/N_+$



VnC Model: Up-voting Probability

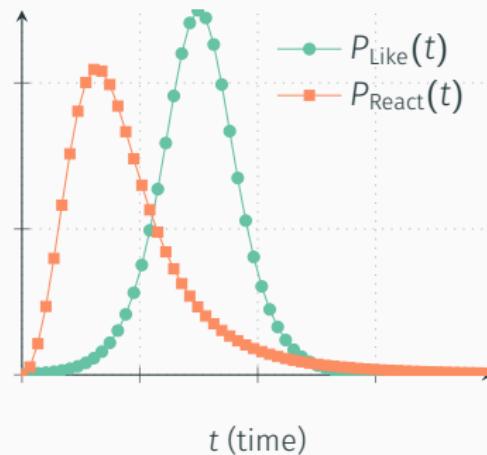
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$P_{\text{React}}(t; \mu, s)$: Probability that a user reacts at time t

- Log-logistic with parameters μ and s

[Details](#)



VnC Model: Up-voting Probability

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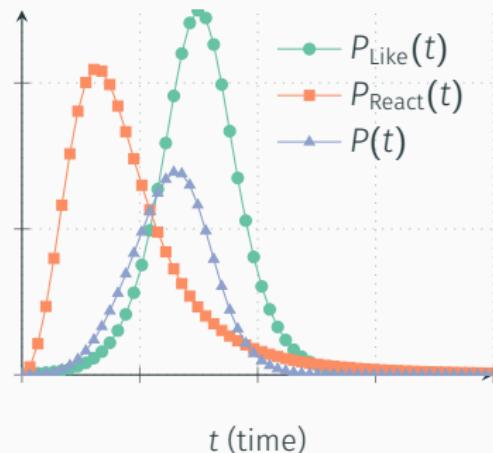
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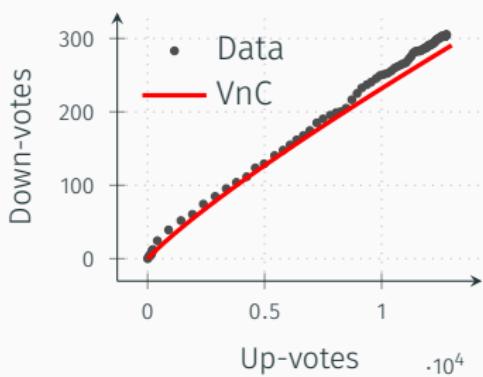
$P(t)$: Probability of a user up-voting at time t

- $P(t) = P_{\text{Like}}(t) \cdot P_{\text{React}}(t)$



VnC Model: Up-votes vs. Down-votes

$$V_-(t+1) = [N_- - V_-(t)] \cdot P_{\text{Like}}(t; \beta_-, \xi_-) \cdot P_{\text{React}}(t; \mu, s)$$



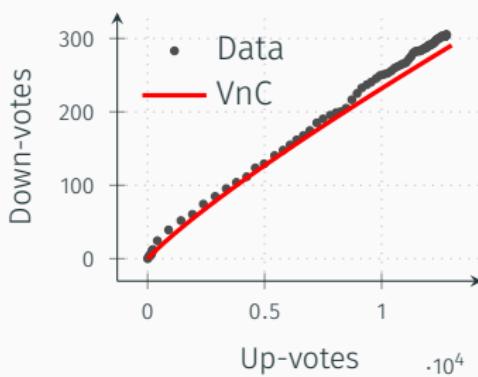
VnC Model: Up-votes vs. Down-votes

$$v_-(t+1) = [N_- - V_-(t)] \cdot \overbrace{P_{\text{Like}}(t; \beta_-, \xi_-)}^{\text{Cascading}} \cdot \overbrace{P_{\text{React}}(t; \mu, s)}^{\text{Reaction Times}}$$

The down-vote time-series

$v_-(t)$ also follows:

1. A cascading mechanism
2. Log-logistic reaction times



VnC Model: Up-votes vs. Down-votes

$$v_-(t+1) = \underbrace{[N_- - V_-(t)]}_{\text{Not-shared Parameters}} \cdot \overbrace{P_{\text{Like}}(t; \beta_-, \xi_-)}^{\text{Cascading}} \cdot \overbrace{P_{\text{React}}(t; \mu, s)}^{\text{Reaction Times}} \cdot \underbrace{s}_{\text{Shared}}$$

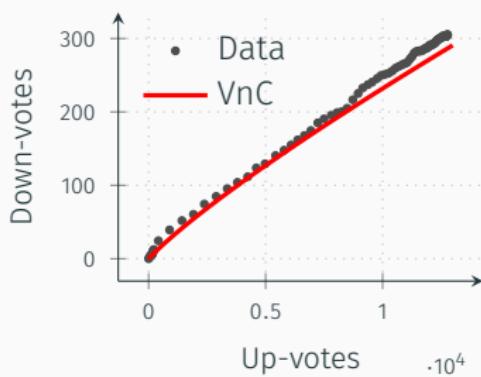
The down-vote time-series

$v_-(t)$ also follows:

1. A cascading mechanism
2. Log-logistic reaction times

Sharing parameters with the up-vote time-series:

1. Shared: μ and s
2. Not shared: N_- , β_- and ξ_-

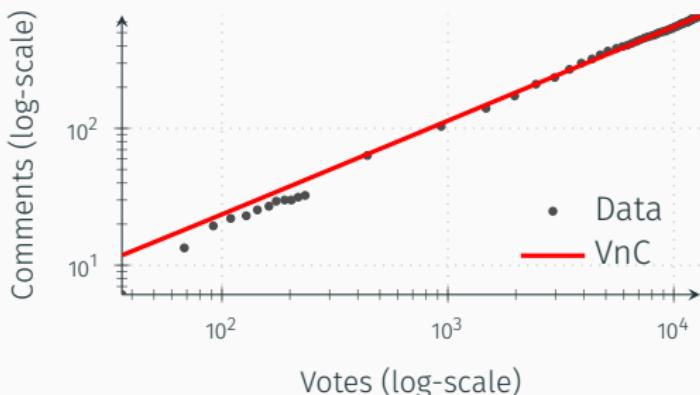


VnC Model: Comments vs. Votes

VnC models the number of comments $C(t)$ as a **power law** on the number of votes:

$$C(t) = k \cdot [V_+(t) + V_-(t)]^\alpha$$

The power-law — matches the data



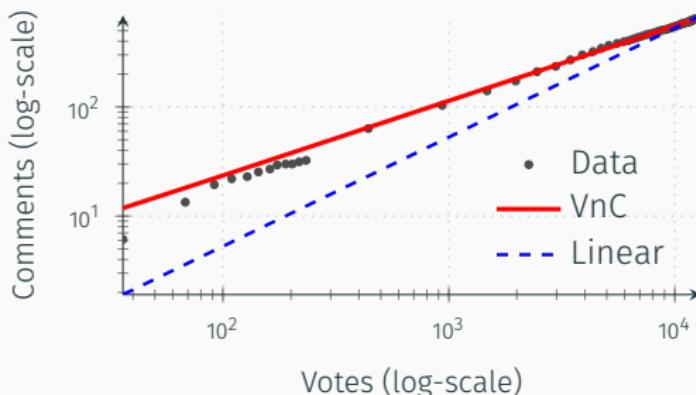
VnC Model: Comments vs. Votes

VnC models the number of comments $C(t)$ as a **power law** on the number of votes:

$$C(t) = k \cdot [V_+(t) + V_-(t)]^\alpha$$

The power-law — red — matches the data

- The linear relationship fails to match the data



VnC Model: Experiments – Questions

Our goal is to answer the following questions:

- **Q1 – Fit Accuracy:** Is VnC more accurate than existing models when fitting social voting data?
- **Q2 – Popularity Decay:** Can VnC model the popularity decay of submissions?
- **Q3 – Coevolution:** Can VnC model the coevolution of up-votes, down-votes and comments time-series?

VnC Model: Experiments – Datasets

Our crawler tracked Reddit and Imgur submissions:

- Collected the number of votes and comments every 20 minutes
- Submissions were tracked for 33 hours after their creation
- Submissions with less than 100 up-votes were discarded

Digg dataset publicly available (Lerman and Ghosh, 2010):

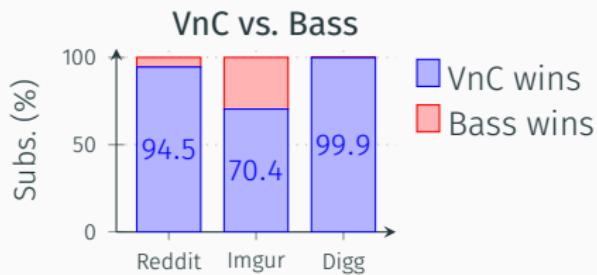
- Only up-votes (no down-votes and comments data)

Dataset	# Submissions	# User Interactions
Reddit	17,205	113,331,266
Imgur	724	2,107,576
Digg	3,553	5,149,170

VnC Model: Experiments – Q1. Fit Accuracy

Percentage of up-vote time-series that were best fit by each model

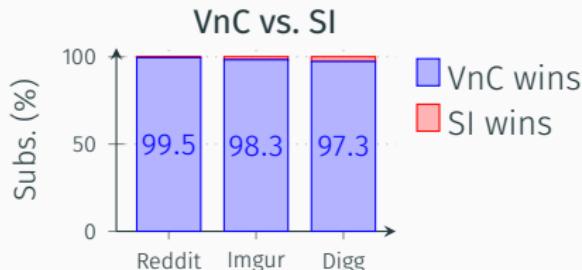
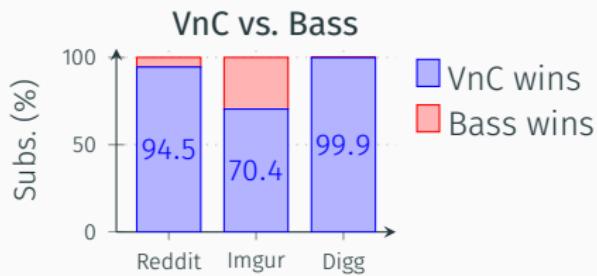
- Best fit determined by smaller root-mean-square error [Details](#)



VnC Model: Experiments – Q1. Fit Accuracy

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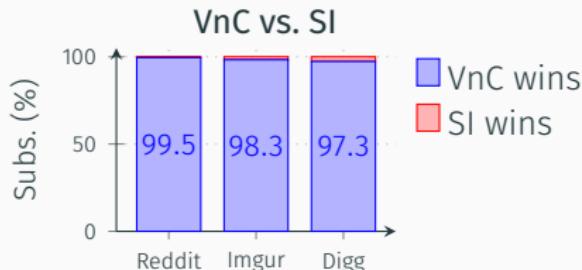
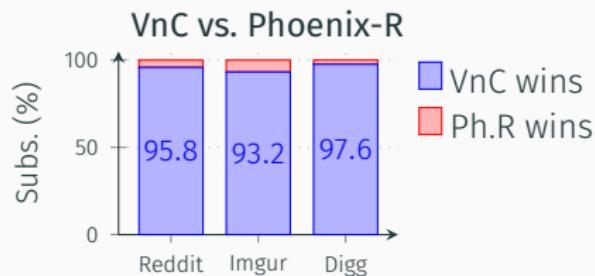
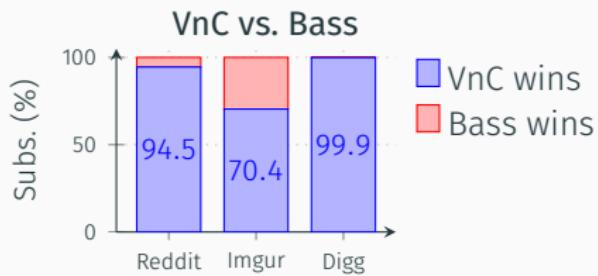
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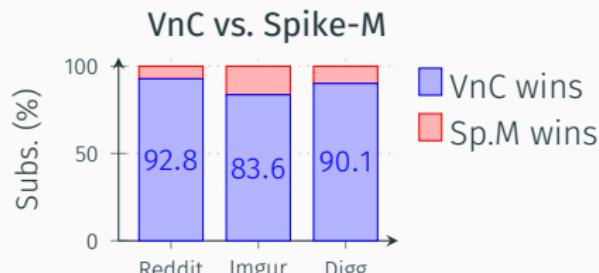
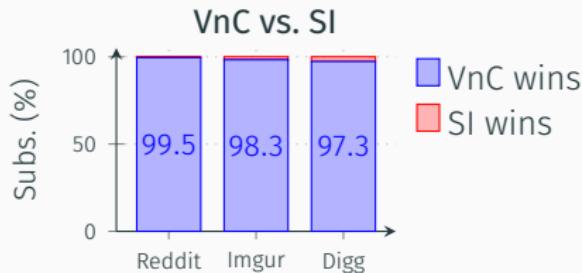
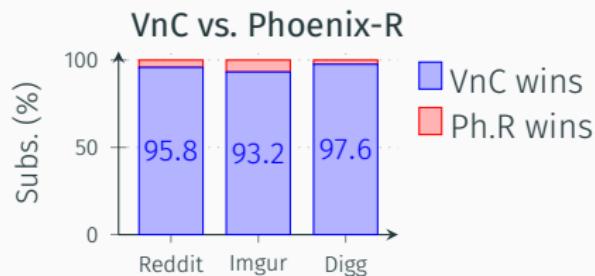
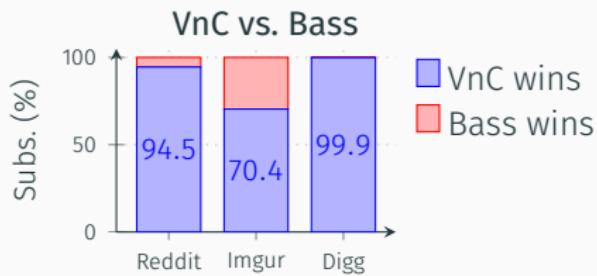
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VnC Model: Experiments – Q1. Fit Accuracy

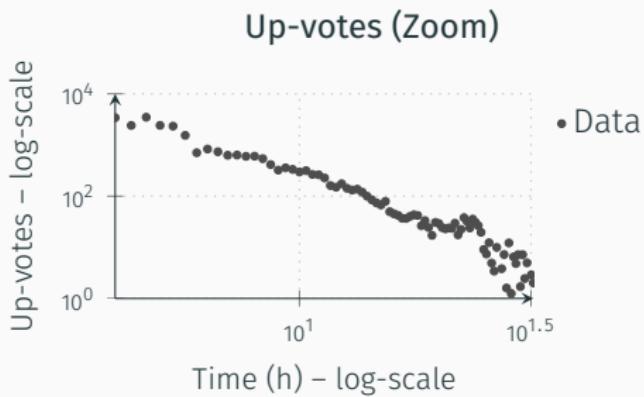
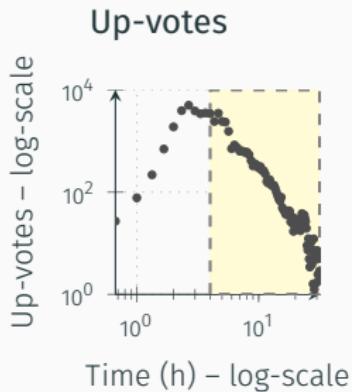
Percentage of up-vote time-series that were best fit by each model

- Best fit determined by smaller root-mean-square error [Details](#)



VnC Model: Experiments – Q2. Popularity Decay

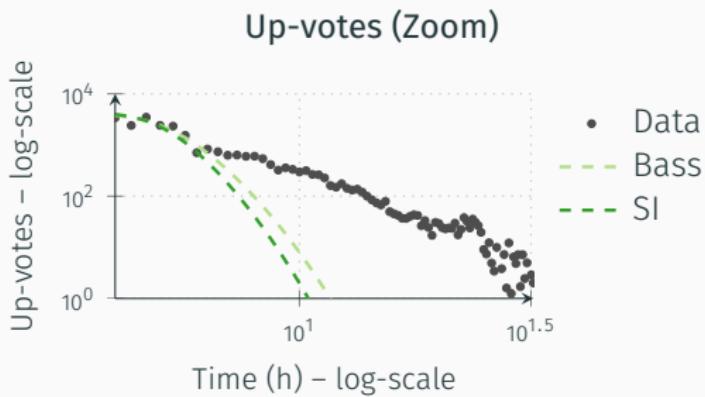
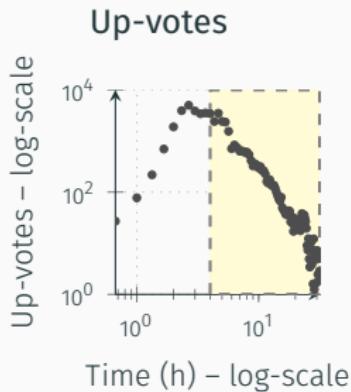
Up-vote time-series have a heavy-tail decay



VnC Model: Experiments – Q2. Popularity Decay

Up-vote time-series have a heavy-tail decay

Bass and SI models generate unrealistic exponential decays

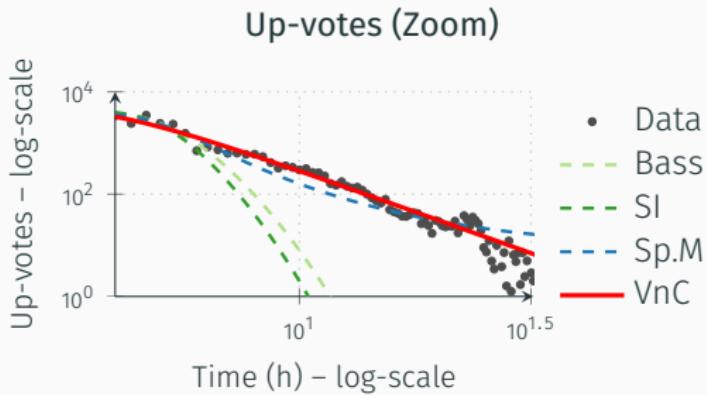
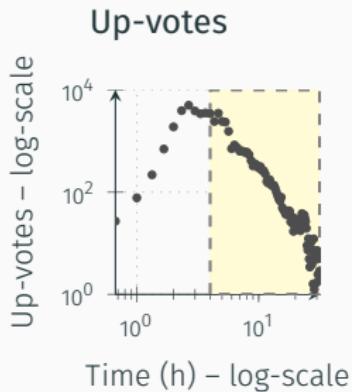


VnC Model: Experiments – Q2. Popularity Decay

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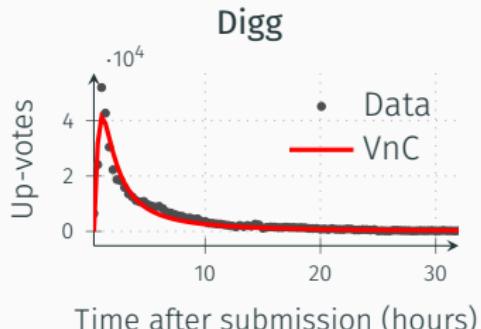
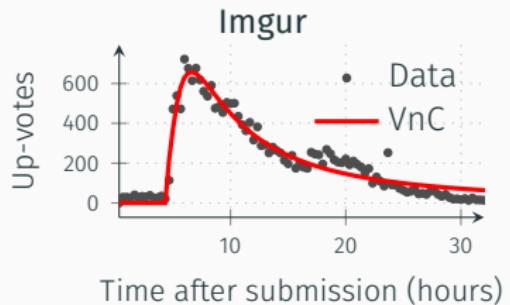
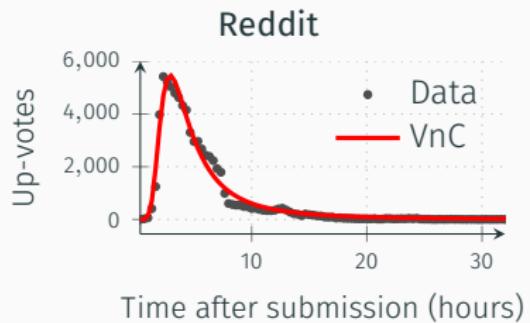
Bass and SI models generate unrealistic exponential decays

VnC and Spike-M are able to match the heavy tail decay



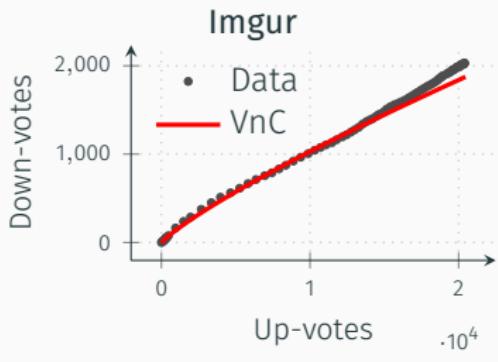
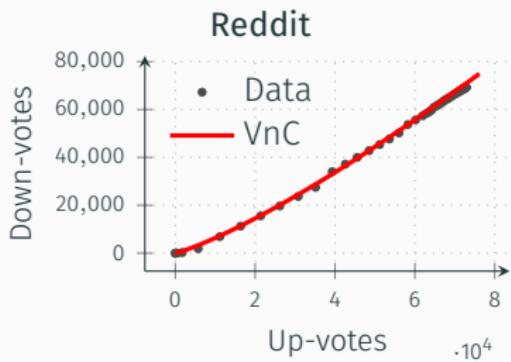
VnC Model: Experiments – Q3. Coevolution

VnC up-vote time-series fits for the most voted submissions in each dataset



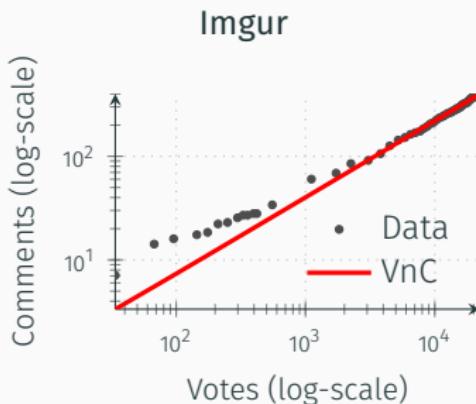
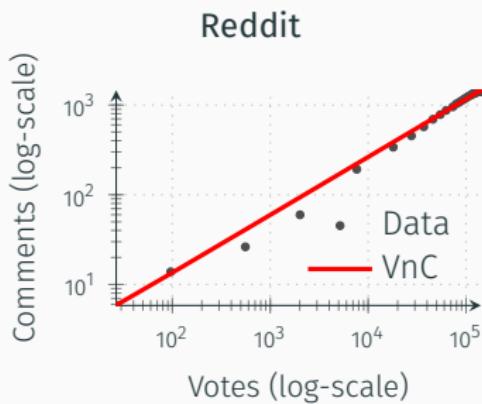
VnC Model: Experiments – Q3. Coevolution

VnC fit for the relationship between up-votes and down-votes received by a submission



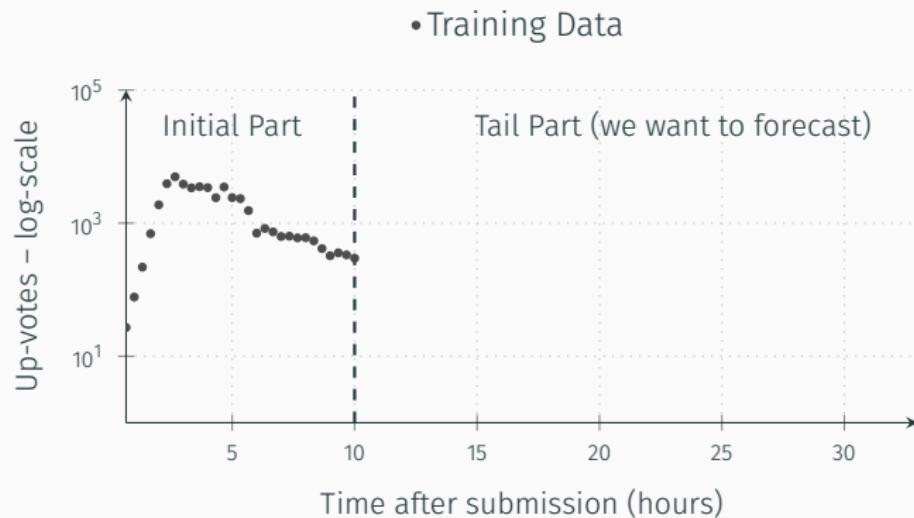
VnC Model: Experiments – Q3. Coevolution

VnC fit for the relationship between total votes (up-votes + down-votes) and comments received by a submission



VnC Model: Applications – Forecasting

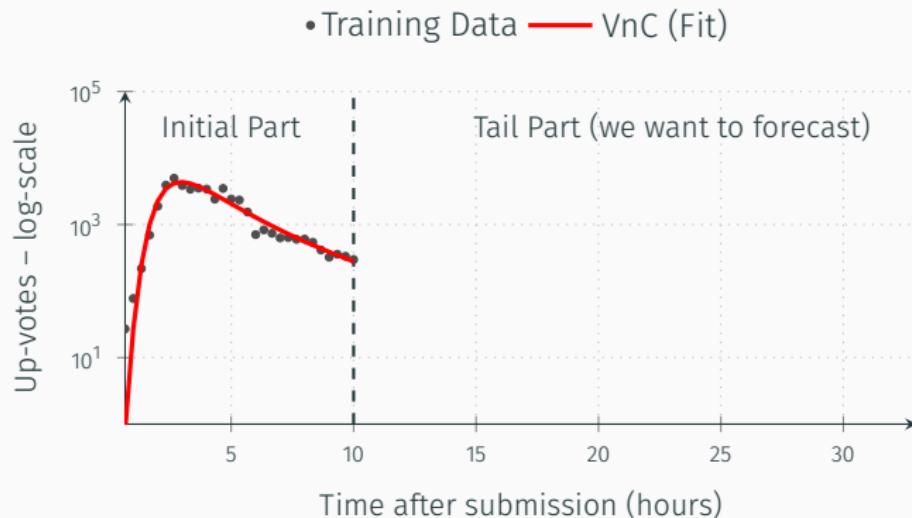
Problem: Given the initial part of a social voting time-series, predict the tail part



VnC Model: Applications – Forecasting

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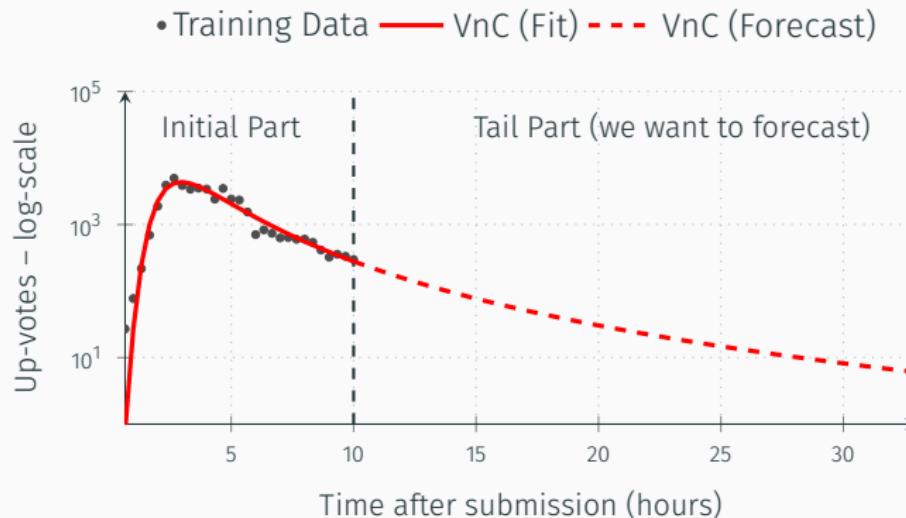
1. Estimate VnC parameters using the initial part



VnC Model: Applications – Forecasting

Problem: Given the initial part of a social voting time-series, predict the tail part

1. Estimate VnC parameters using the initial part
2. Use the parameters to forecast the tail part

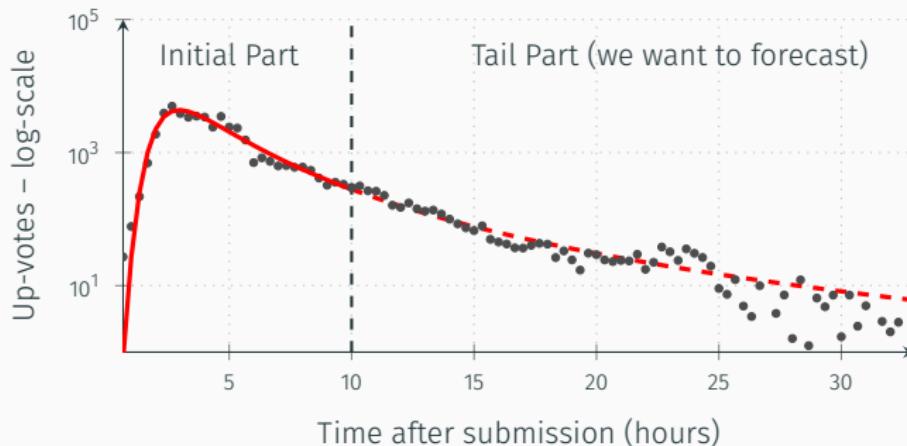


VnC Model: Applications – Forecasting

Problem: Given the initial part of a social voting time-series, predict the tail part

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2. Use the parameters to forecast the tail part

• Training Data — VnC (Fit) - - - VnC (Forecast) • Tail Data



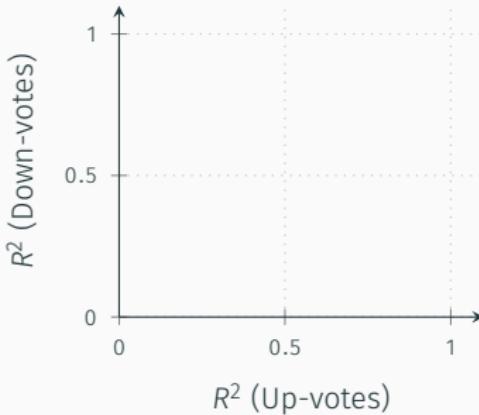
VnC Model: Applications – Outlier Detection

To detect outliers we use

VnC's R^2

- R^2 measures fit accuracy
- R^2 values closer to 1 indicate better fits

R^2 vs. R^2 plot:



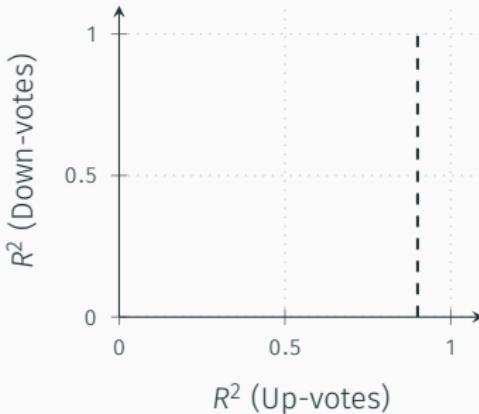
VnC Model: Applications – Outlier Detection

To detect outliers we use
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R^2 vs. R^2 plot:

1. Compute R^2 for the up-vote time-series



VnC Model: Applications – Outlier Detection

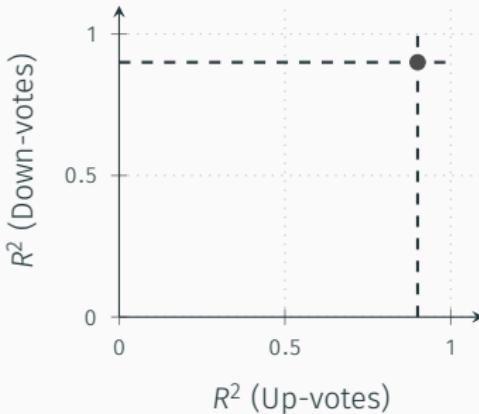
To detect outliers we use

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R^2 vs. R^2 plot:

1. Compute R^2 for the up-vote time-series
2. Compute R^2 for the down-vote time-series



VnC Model: Applications – Outlier Detection

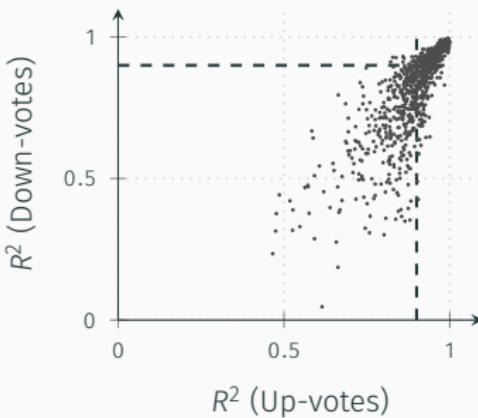
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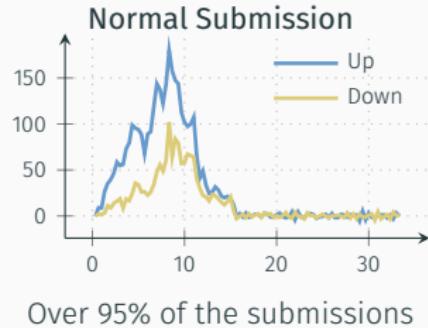
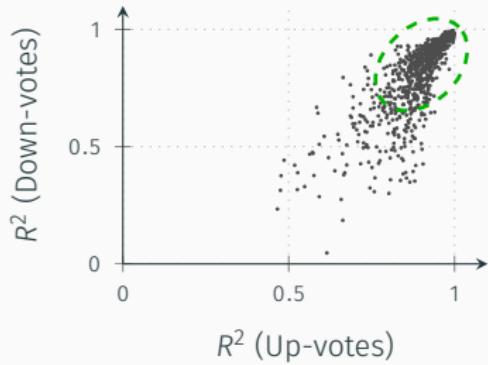
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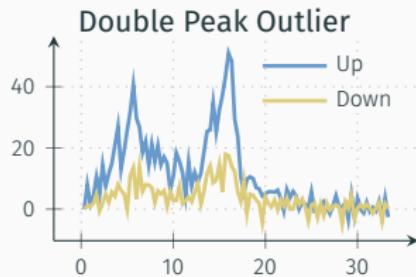
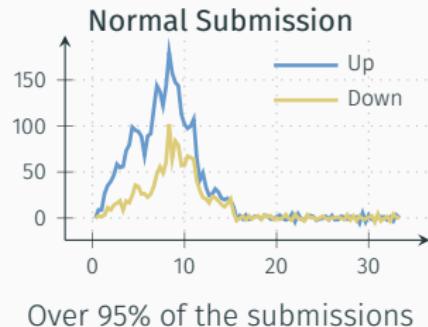
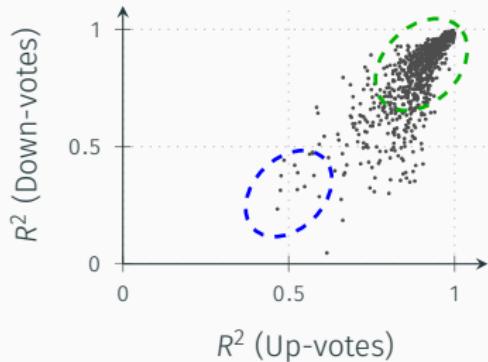
1. Compute R^2 for the up-vote time-series
2. Compute R^2 for the down-vote time-series
3. Repeat for all submissions



VnC Model: Applications – Outlier Detection

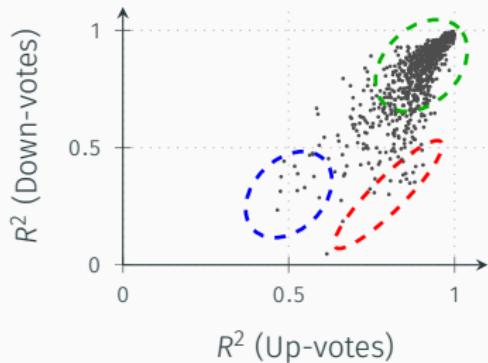


VnC Model: Applications – Outlier Detection

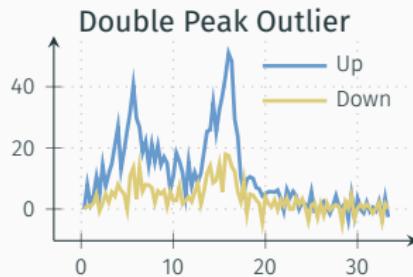


Late-night submissions: 1st peak at night, 2nd peak at morning

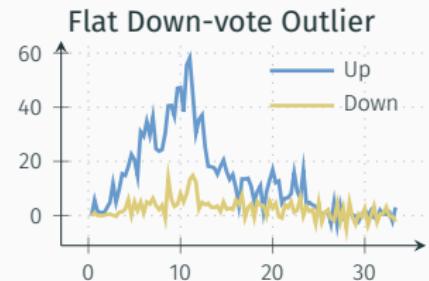
VnC Model: Applications – Outlier Detection



Over 95% of the submissions

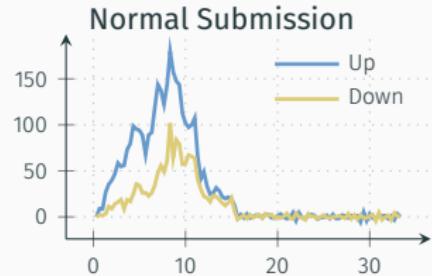
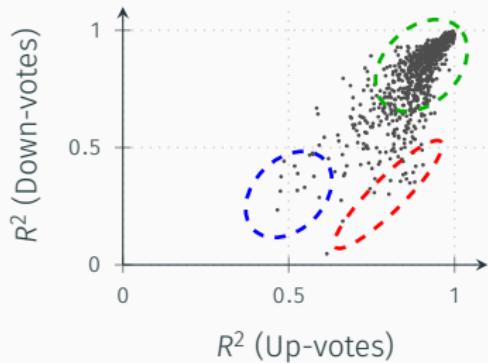


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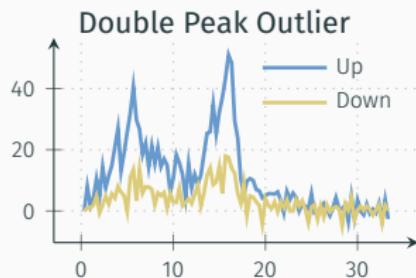


Most are pictures of animals

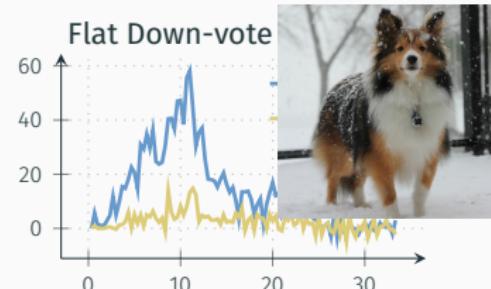
VnC Model: Applications – Outlier Detection



Over 95% of the submissions



Late-night submissions: 1st peak at night, 2nd peak at morning



Most are pictures of animals

VnC Model: Summary

VnC has the following advantages:

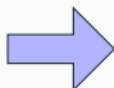
- **Coevolution Modeling:** Describes up-vote, down-vote and comments time-series
- **Practicality:** Matches data from several social voting web sites
- **Usefulness:** Forecasting and outlier detection

Outline

1. Introduction
2. Contribution 1: the Act-M Model
3. Contribution 2: the VnC Model
4. Contribution 3: the MFS-Map Method
5. Conclusions

MFS-Map: Introduction

How can we automatically find a set of textual annotations to describe a social media image?



Annotations

Gyeongju, Korea,
Temple, Bulguksa

Important Applications:

- Image search (even if we have only visual content)

MFS-Map: Introduction

Given a vocabulary of annotations:

- $\mathcal{A} = \{\text{animals}, \text{baby}, \text{bird}, \text{car}, \text{clouds}, \dots, \text{water}\}$

Ask people to assign relevant annotations to an image:



animals, bird, sky

Goal: use annotated images to **automatically learn** how to annotate new images

- Crowd-sourcing is not always free/available!

MFS-Map: Problem Definition

Input: social media image \mathcal{I} ,
consisting of:

- An image I (i.e. a matrix of pixels)
- A set of textual tags
 $L = \{\ell_1, \ell_2, \dots\}$

Input Image, I



Tags, $L = \{\ell_1, \ell_2, \dots\}$

crane, gru, sunset,
hdr, tramonto, ...

Output: set of textual image annotations $A = \{a_1, a_2, \dots\}$

Note: tags \neq annotations

- Tags: subjective, noisy, missing...
- Annotations: describe the images' visual content

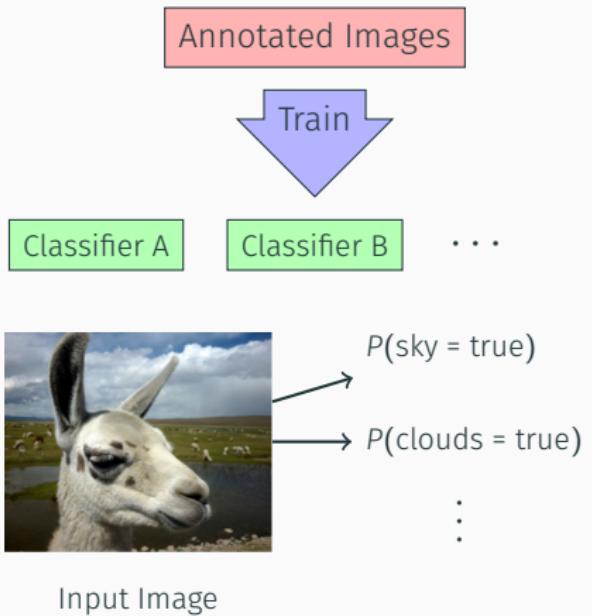
Annotations, $A = \{a_1, a_2, \dots\}$

sky, clouds,
sunset, ...

MFS-Map: Baseline Solution

Baseline Solution:

1. Train a binary classifier for each possible annotation
2. Given an input image, predict the relevance of each annotation



Problems:

- Class imbalance
- High computational cost

The MFS-Map is divided into three steps:

1. Feature Discretization

- **Goal:** learn a map function that maps images to sets of discrete feature items

2. Rule Generation

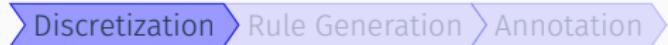
- **Goal:** learn rules that associate visual features and tags to annotations

3. Prediction of Annotation Relevance

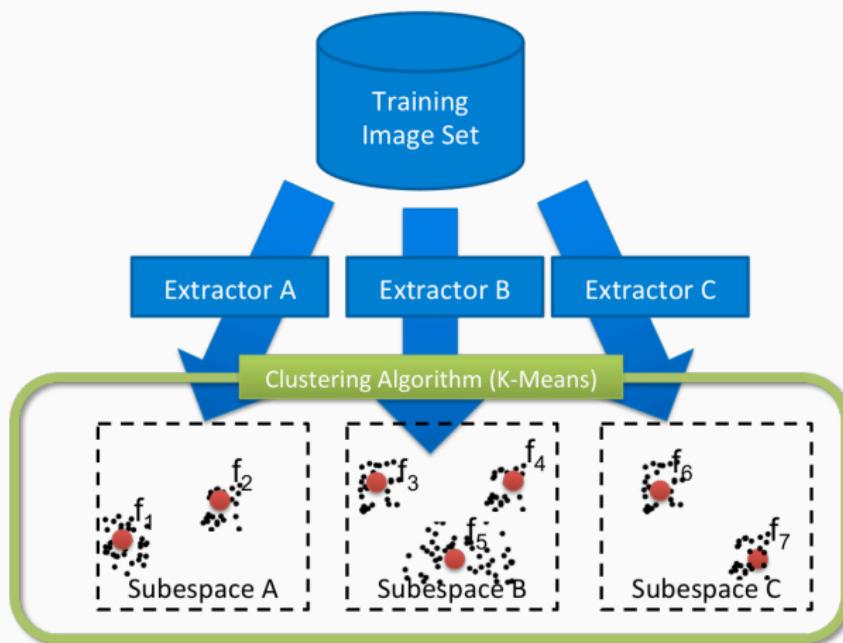
- **Goal:** use the rules to assign annotations to images

MFS-Map: Visual Feature Discretization

MFS-Map:



Learning the map function:

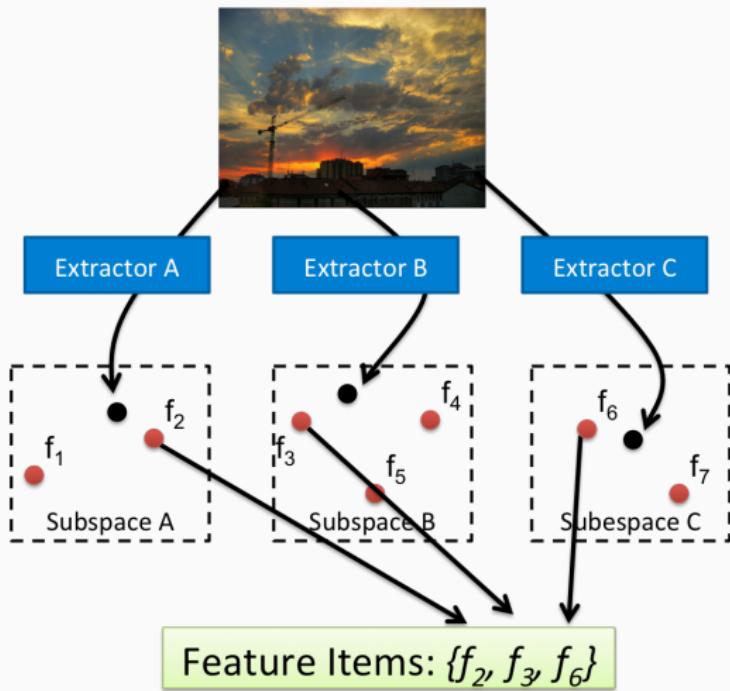


MFS-Map: Visual Feature Discretization

MFS-Map:



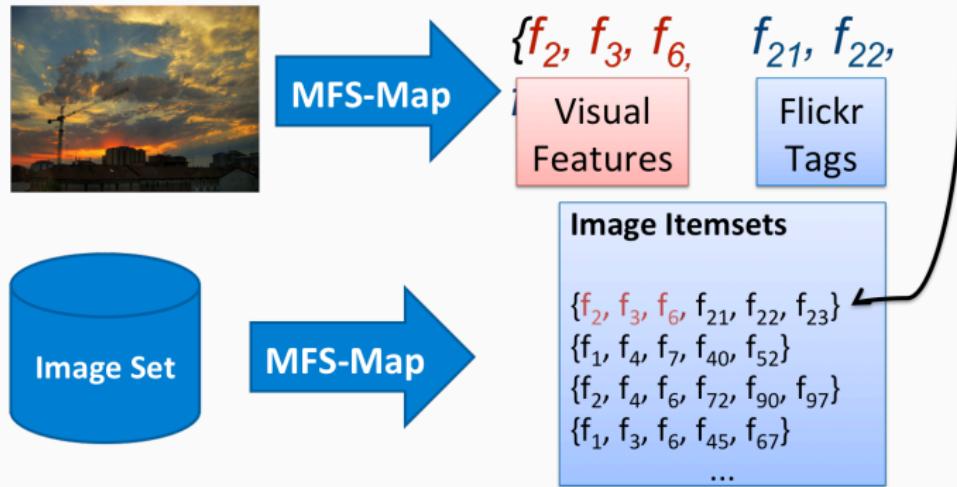
1. Feature vector extraction
 - Each ● represents a feature vector
2. Find the nearest **reference vector**
 - Each ● f_i corresponds to a feature item
3. Generate the feature items



MFS-Map: Rule Generation

MFS-Map: Discretization → Rule Generation → Annotation

Itemset representation: MFS-Map combines tags and visual features of an image into an itemset representation:



MFS-Map: Rule Generation

MFS-Map:



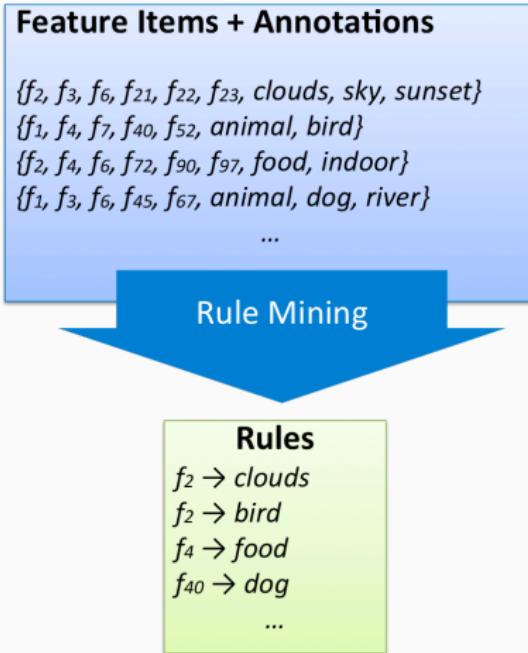
1. Combine feature items and annotations

2. Generate all rules in the format:

$$f_i \rightarrow a_k$$

f_i : feature item

a_k : annotation



MFS-Map: Rule Generation

MFS-Map: Discretization > Rule Generation > Annotation

For each rule, compute its confidence:

- Compute the confidence of all pairs $\text{conf}(f_i, a_j)$
- Not all pairs may occur on the dataset: use a hash-map to save memory

$$\text{conf}(f_i, a_j) = \frac{\# \text{ itemsets containing } f_i \text{ and } a_j}{\# \text{ itemsets containing } f_i}$$

Discard rules with $\text{conf} < \text{minConf}$

- minConf is a threshold (user defined parameter)

MFS-Map: Annotation

MFS-Map:



1. Extract image itemset
2. Find matching rules
3. For each annotation compute the mean confidence
 - sunset = 0.88
 - city = 0.72
 - animal = 0.00



Mined rules:

$\{f_1\} \rightarrow \{\text{'animal'}\}$	(conf = 0.67)
✓ $\{f_4\} \rightarrow \{\text{'sunset'}\}$	(conf = 0.82)
✓ $\{f_2\} \rightarrow \{\text{'city'}\}$	(conf = 0.42)
✓ $\{f_5\} \rightarrow \{\text{'sunset'}\}$	(conf = 0.93)

MFS-Map: Experiments

Datasets (Flickr images):

1. **MIR-Flickr:** 25,000 images / 25 annotations
2. **Image CLEF:** 18,000 images / 98 annotations

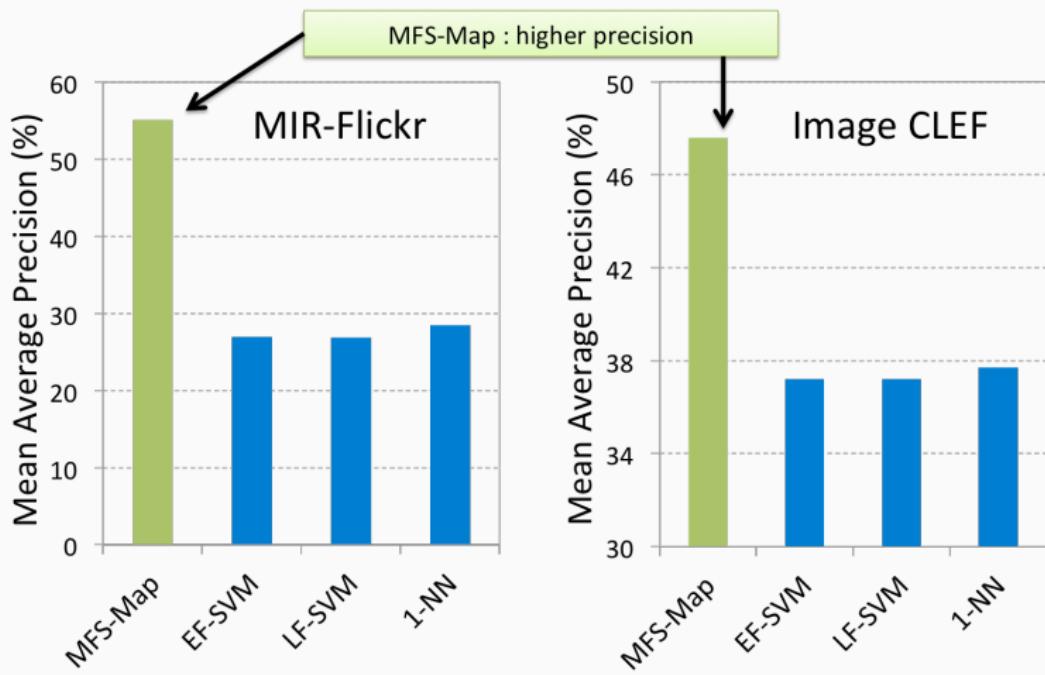
Annotation methods:

- **MFS-Map** (proposed method)
- **EF-SVM:** Binary classifier + Early Fusion
- **LF-SVM:** Binary classifier + Late Fusion
- **1-NN:** Nearest neighbors

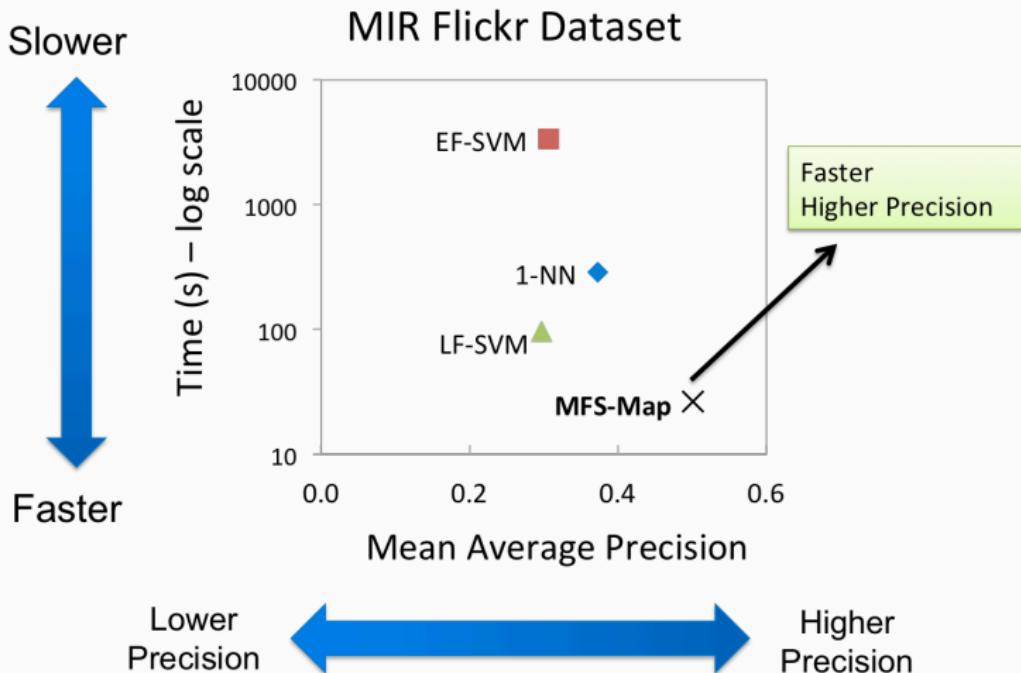
Features:

- Visual: SIFT, Gist, SFTA (texture), RGB histogram
- Flickr user tags

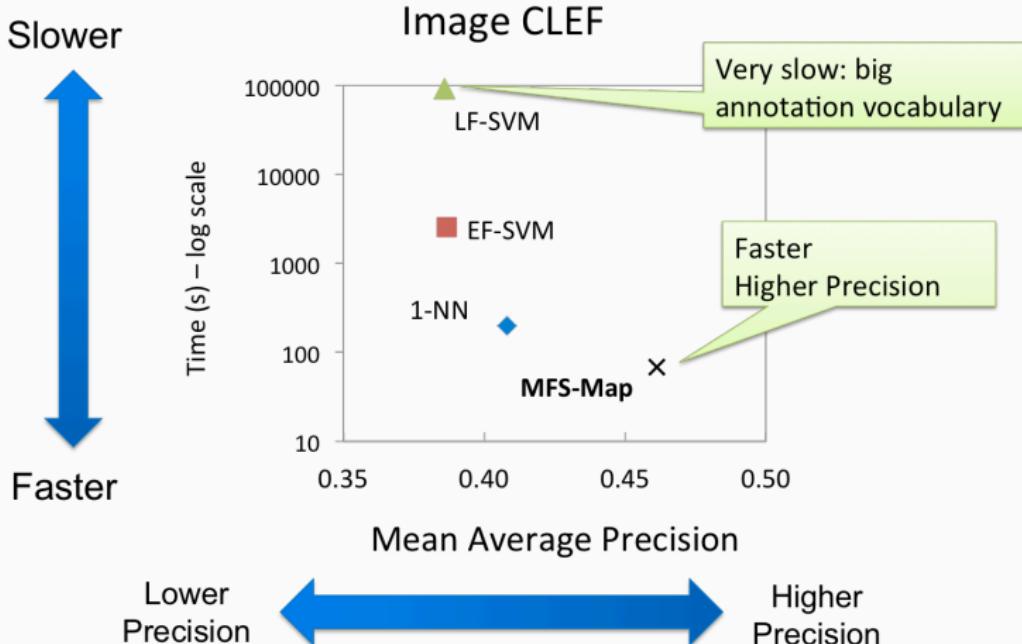
MFS-Map: Experiments



MFS-Map: Experiments



MFS-Map: Experiments



MFS-Map highlights:

1. **Feature Combination:** is able to annotate images using both visual and textual features
2. **Scalability:** faster than techniques based on classifiers
3. **Precision:** competitive precision results in publicly available datasets

Outline

1. Introduction
2. Contribution 1: the Act-M Model
3. Contribution 2: the VnC Model
4. Contribution 3: the MFS-Map Method
5. Conclusions

Conclusions

Main contributions:

1. Act-M Model:

- Describes activity patterns that we observed in the IAT distribution of users' postings
- Can be used to detect bots based only on time-stamp data

2. VnC Model:

- Describes the coevolution of user interactions (up-votes, down-votes and comments) in social voting services

3. MFS-Map Method:

- Automatically annotate social media images by efficiently combining visual and textual information

Publications

Main publications:

- Act-M Model:
 - Conference paper: ACM KDD
 - Journal paper: ACM TKDD
- VnC Model:
 - Conference paper: IEEE ICDM
- MFS-Map Method:
 - Conference paper: ACM SAC

Collaborations:

- Anomaly detection (VolTime method):
 - Conference paper: SIAM SDM
- Computer vision (fire and lung disease detection):
 - Conference papers: ACM SAC, ICEIS and CBMS

Thank you!

Mining user activity data in social media services

Alceu Ferraz Costa

Supervisor: Prof. Dr. Agma Juci Machado Traina

Co-supervisor: Prof. Dr. Christos Faloutsos

Funding:



VnC Model: Reaction Probability (Details)

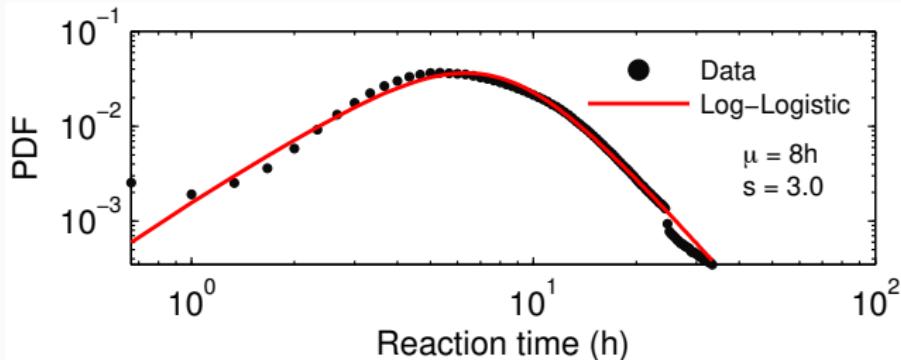
Definition (Reaction Time)

The reaction time corresponds to the time interval between the instant in which a submission is created and the instant in which an interaction (vote or comment) occurs.

Data: Reaction times of up-votes, down-votes and comments from the Reddit, Imgur and Digg datasets.

Log-Logistic PDF

$$f(x) = \frac{(s/\mu)(x/\mu)^{s-1}}{(1 + (x/\mu)^s)^2}$$



VnC Model: Fit Accuracy (Details)

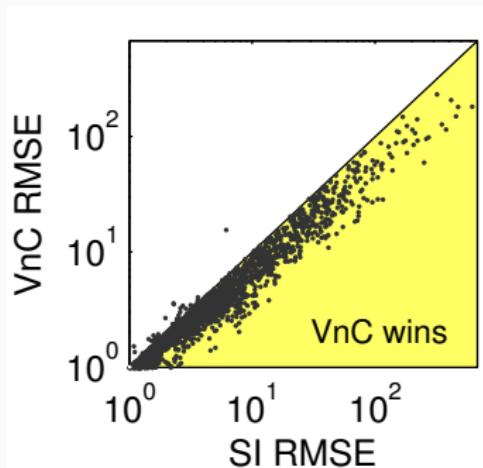
Root-Mean-Square Error

- Lower RMSE indicates a better fit
- Points below the diagonal: time-series that were best fit by VnC

Is VnC more accurate than:

- SI Model? Yes
- Bass Model?
- Phoenix-R?
- Spike-M?

VnC vs. SI Model



VnC is more accurate than
SI model for 99%
of the submissions

VnC Model: Fit Accuracy (Details)

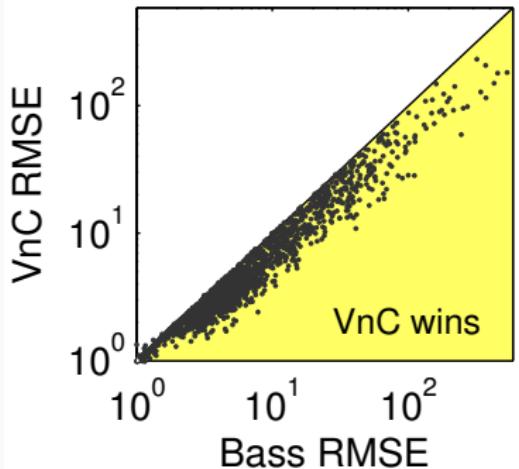
Root-Mean-Square Error

- Lower RMSE indicates a better fit
- Points below the diagonal: time-series that were best fit by VnC

Is VnC more accurate than:

- SI Model? Yes
- Bass Model? Yes
- Phoenix-R?
- Spike-M?

VnC vs. Bass Model



VnC is more accurate than Bass Model for 91% of the submissions

VnC Model: Fit Accuracy (Details)

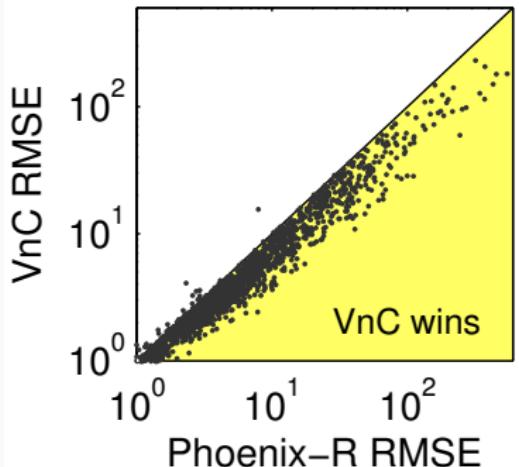
Root-Mean-Square Error

- Lower RMSE indicates a better fit
- Points below the diagonal: time-series that were best fit by VnC

Is VnC more accurate than:

- SI Model? Yes
- Bass Model? Yes
- Phoenix-R? Yes
- Spike-M?

VnC vs. Phoenix-R



VnC is more accurate than Phoenix-R for 96% of the submissions

VnC Model: Fit Accuracy (Details)

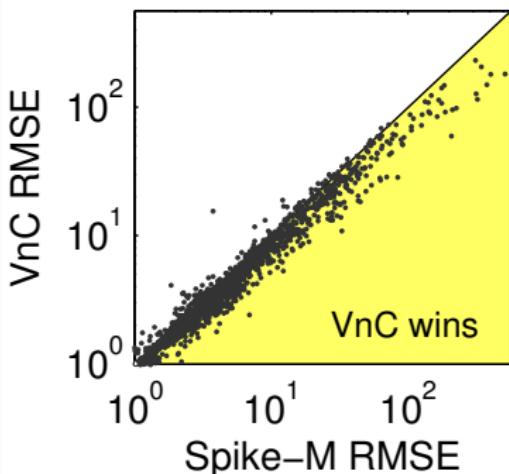
Root-Mean-Square Error

- Lower RMSE indicates a better fit
- Points below the diagonal: time-series that were best fit by VnC

Is VnC more accurate than:

- SI Model? Yes
- Bass Model? Yes
- Phoenix-R? Yes
- Spike-M? Yes

VnC vs. Spike-M



VnC is more accurate than Spike-M for 90% of the submissions