Are you ready for the Era of Big Data?

CEDT Meeting

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Aug 08, 2012

Introduction

custard powder

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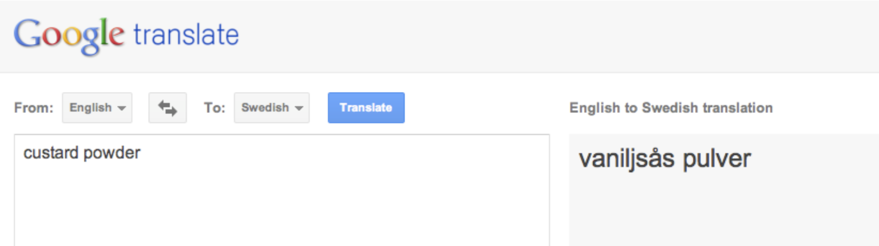
custard powder



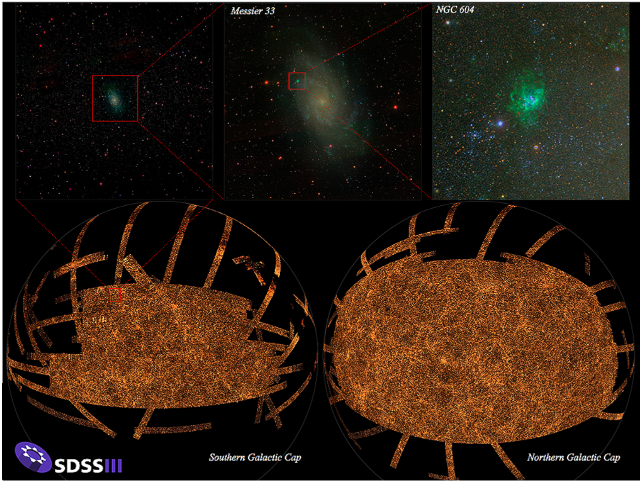
How does Google Translate work?

- Does not use Rules
- Uses Statistical Machine Translation
- Statistical models are trained from large corpora

Outline

What is BigData

(Source: Wikipedia)
Sloan Digital Sky Survey has amassed data of 1.4 TeraBytes.
Need to process 200GB per night.



Examples of BigData

- Large Hadron Collider 13000 Terabytes
- Walmart handles 1 million customer transactions every hour, 2.5 petabytes
- Biology Human genome project took 10 years, now it can be done in one week

What is Big Data?

No precise definition

Working Definition

Datasets so large and complex that they become awkard using on-hand database management tools

Challenges

- capture
- storage
- sharing
- analysis
- visualization

The era of Big Data is upon us

Message from the president(June 2011)
(International Society for Bayesian Analysis)
Prof. M. I. Jordan, Dept of Statistics, UC Berkeley

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In science, massive streams of data have become the norm in areas such as astronomy, high-energy physics, ecology, genetics and molecular biology.

Companies are increasingly looking to hire people who have expertise in data analysis.While the job descriptions sometimes refer to statistics they often refer to data analytics, data mining and machine learning.

Are you ready for big data?

Mckinsey Report

Businesses can gain more if they exploit and understand BigData

Huge Demand for Engineers who can effectively address issues related to Big Data.

Big Data needs Data Scientist

Posted on LinkedIn, 25th June 2012

Data Scientist- "Machine Learning"

Amazon - Bengaluru Area, India

amazon

Job Description

Online advertising is set to become a $100 billion market.Our Advertising Technologies group is building the infrastructure to meet theneeds of advertisers and publishers in this rapidly changing industry. We poweradvanced online advertising programs for some of the world's largest websites,including Amazon.com and other prime online properties. We supply thetechnology to show the right ad to the right customer at the right time.

The Traffic Validation team in Bangalore is part ofAdvertising technology group and is completely responsible for ensuring hightraffic quality for multiple ad-programs within Amazon. We build systems thatprocess vast amounts of data of the order of tera-bytes on daily basis, usingadvanced algorithms in data mining , machine learning, and statisticalanalysis. Our distributed systems are built on cutting edge scalabletechnologies such as Hadoop and Amazon's EC2 and S3 cloud services.

The data scientist responsible for solving complexlarge-data problems in online advertising fraud space using data mining,machine learning and statistical analysis. We are looking for a highlymotivated individuals who are passionate to apply research to solve actualbusiness problems in fraud and spam detection space. The role involves analyzinglarge datasets which run into billions of records per day, mine patterns in thedata and build models that can detect fraudulent and spam traffic. An idealcandidate should be able to analyze traffic patterns on platforms like Hadoopand develop scalable and low latency models that can detect the patterns.

Phd/MTech/MS or equivalent degree in Computer Science orMathematics or Statistics
2-5 year relevant industry or research experience

Skill Set

Responsibilities

Solve complex large-data problems in online advertising fraud space using data mining,machine learning and statistical analysis. Design algorithms which can handle Tera-Bytes of data on a daily basis in a cloud computing.

- PhD/Masters in CS/Maths/Statistics
- Knowledge of Hadoop and other distributed computing platform
- Experience with Analysis on large scale datasets

Takeaway

Need firm grounding in

- Machine Learning
- Statistics
- Distributed Optimization

Ability to build systems

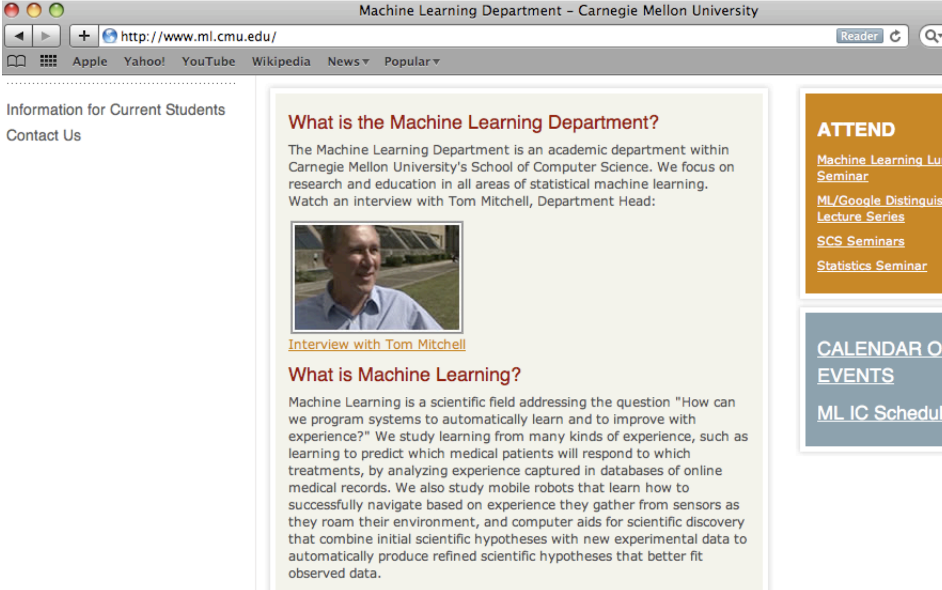
Takeaway

Need firm grounding in

- Machine Learning
- Statistics
- Distributed Optimization

Ability to build systems Why not come to IISc?

What is Machine Learning?


Machine Learning Department – Carnegie Mellon University

http://www.ml.cmu.edu/

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Information for Current Students

Contact Us

What is the Machine Learning Department?

The Machine Learning Department is an academic department within Carnegie Mellon University's School of Computer Science. We focus on research and education in all areas of statistical machine learning. Watch an interview with Tom Mitchell, Department Head:

Interview with Tom Mitchell

What is Machine Learning?

Machine Learning is a scientific field addressing the question "How can we program systems to automatically learn and to improve with experience?" We study learning from many kinds of experience, such as learning to predict which medical patients will respond to which treatments, by analyzing experience captured in databases of online medical records. We also study mobile robots that learn how to successfully navigate based on experience they gather from sensors as they roam their environment, and computer aids for scientific discovery that combine initial scientific hypotheses with new experimental data to automatically produce refined scientific hypotheses that better fit observed data.

ATTEND

Machine Learning Lu

Seminar

ML/Google Distinguis

Lecture Series

SCS Seminars

Statistics Seminar

CALENDAR O

EVENTS

ML IC Schedu

What is Machine Learning?(CMU ML Dept)

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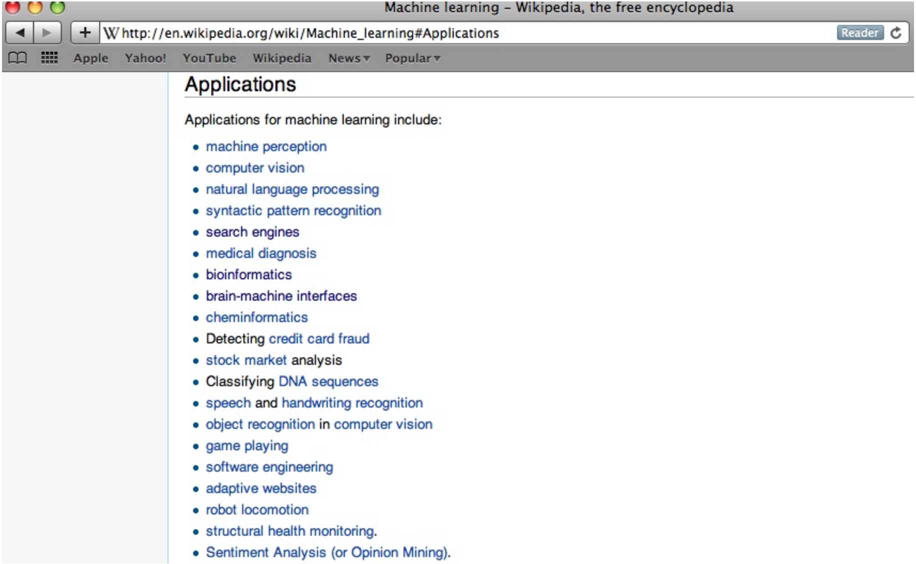
Scope of Machine Learning


Machine learning - Wikipedia, the free encyclopedia

http://en.wikipedia.org/wiki/Machine_learning#Applications

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Applications

Applications for machine learning include:

- machine perception
- computer vision
- natural language processing
- syntactic pattern recognition
- search engines
- medical diagnosis
- bioinformatics
- brain-machine interfaces
- cheminformatics
- Detecting credit card fraud
- stock market analysis
- Classifying DNA sequences
- speech and handwriting recognition
- object recognition in computer vision
- game playing
- software engineering
- adaptive websites
- robot locomotion
- structural health monitoring.
- Sentiment Analysis (or Opinion Mining).

Predictive models

- $y = \{1, -1\}$ binary Classification

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- Ordinal regression
- Regression

Predictive models

- $y = \{1, -1\}$ binary Classification
- $y = \{1, \ldots, k\}$ multi-category classification
- Ordinal regression
- Regression
- Reinforcement learning

Predictive models

- Need to quantify the fit between the target y and the prediction $f(x)$ on D

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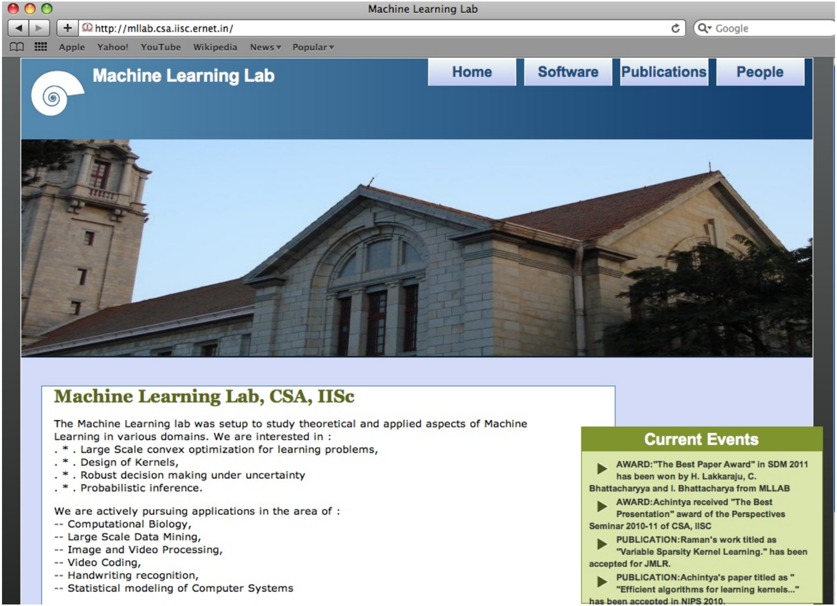
- Need to quantify the fit between the target y and the prediction $f(x)$ on D
- the model should hold for all x, even on data not present in D sometimes called *generalization ability*.
- The problem now becomes finding a model f, which *generalizes well* and fits the training data

What we do at IISc



What we do at IISc

- Large Scale convex optimization for learning problems,
- Design of Kernels
- Robust decision making under uncertainty
- Probabilistic inference
- Computational Biology,
- Image and Video Processing,
- Statistical modeling of Computer Systems
- Large Scale Text Mining

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Discovery of Application Workloads from Network File Traces
Yadwadkar N. , Bhattacharyya C., K. Gopinath, N. Thirumale, S. Susarla
FAST 2010

Focusing on the Opcode Sequence

Time Stamp	Source IP	Destination IP	OPCODE	Parameters
01:39:39.146061	10.192.25.47	-> 10.192.25.18 NFS V3	LOOKUP	all, DH:0x7c58939e/.Trash
01:39:39.146099	10.192.25.18	-> 10.192.25.47 NFS V3	LOOKUP	eply (Call In 12) Error:NFS3ERR_NOENT
01:39:39.146667	10.192.25.47	-> 10.192.25.18 NFS V3	LOOKUP	all, DH:0x7c58939e/.Trash-1003
01:39:39.146701	10.192.25.18	-> 10.192.25.47 NFS V3	LOOKUP	eply (Call In 14) Error:NFS3ERR_NOENT
01:39:39.151332	10.192.25.47	-> 10.192.25.18 NFS V3	ACCESS	ll, FH:0x7c58939e
01:39:39.151381	10.192.25.18	-> 10.192.25.47 NFS V3	ACCESS	eply (Call In 16)
01:39:39.152028	10.192.25.47	-> 10.192.25.18 NFS V3	LOOKUP	all, DH:0x7c58939e/.Trash-1001
01:39:39.152072	10.192.25.18	-> 10.192.25.47 NFS V3	LOOKUP	eply (Call In 18) Error:NFS3ERR_NOENT
01:39:42.115414	10.192.25.47	-> 10.192.25.18 NFS V3	GETATTR	Call, FH:0xe21586f0
01:39:42.115481	10.192.25.18	-> 10.192.25.47 NFS V3	GETATTR	Reply (Call In 69) Regular File mode:0755 uid:1000 gid:1000
01:39:42.115999	10.192.25.47	-> 10.192.25.18 NFS V3	READ	FH:0xe21586f0 Offset:0 Len:16384
01:39:42.116050	10.192.25.18	-> 10.192.25.47 NFS V3	READ	y (Call In 72) Len:16384[Unreassembled Packet [incorrect TCP checksum]]
01:39:42.118382	10.192.25.47	-> 10.192.25.18 NFS V3	GETATTR	Call, FH:0xe21586f0
01:39:42.118423	10.192.25.18	-> 10.192.25.47 NFS V3	GETATTR	Reply (Call In 85) Regular File mode:0755 uid:1000 gid:1000
01:39:42.119314	10.192.25.47	-> 10.192.25.18 NFS V3	LOOKUP	all, DH:0xf21596f0/conf29395.sh
01:39:42.119363	10.192.25.18	-> 10.192.25.47 NFS V3	LOOKUP	eply (Call In 87) Error:NFS3ERR_NOENT
01:39:42.119892	10.192.25.47	-> 10.192.25.18 NFS V3	CREATE	ll, DH:0xf21596f0/conf29395.sh Mode:UNCHECKED
01:39:42.121303	10.192.25.18	-> 10.192.25.47 NFS V3	CREATE	eply (Call In 89)
01:39:42.122465	10.192.25.47	-> 10.192.25.18 NFS V3	WRITE	l, FH:0xe53f81da Offset:0 Len:11 UNSTABLE
01:39:42.122526	10.192.25.18	-> 10.192.25.47 NFS V3	WRITE	ply (Call In 93) Len:11 UNSTABLE
01:39:42.123036	10.192.25.47	-> 10.192.25.18 NFS V3	COMMIT	all, FH:0xe53f81da
01:39:42.128024	10.192.25.18	-> 10.192.25.47 NFS V3	COMMIT	eply (Call In 95)
01:39:42.128539	10.192.25.47	-> 10.192.25.18 NFS V3	GETATTR	Call, FH:0xf21596f0
01:39:42.128575	10.192.25.18	-> 10.192.25.47 NFS V3	GETATTR	Reply (Call In 97) Directory mode:0777 uid:1000 gid:1000
01:39:42.129092	10.192.25.47	-> 10.192.25.18 NFS V3	GETATTR	Call, FH:0xe53f81da
01:39:42.129151	10.192.25.18	-> 10.192.25.47 NFS V3	GETATTR	Reply (Call In 99) Regular File mode:0644 uid:1000 gid:1000
01:39:42.129662	10.192.25.47	-> 10.192.25.18 NFS V3	ACCESS	ll, FH:0xe53f81da
01:39:42.129695	10.192.25.18	-> 10.192.25.47 NFS V3	ACCESS	eply (Call In 101)
01:39:42.130219	10.192.25.47	-> 10.192.25.18 NFS V3	WRITE	l, FH:0xe53f81da Offset:0 Len:18 UNSTABLE
01:39:42.130271	10.192.25.18	-> 10.192.25.47 NFS V3	WRITE	ply (Call In 103) Len:18 UNSTABLE
01:39:42.130772	10.192.25.47	-> 10.192.25.18 NFS V3	COMMIT	all, FH:0xe53f81da
01:39:42.135557	10.192.25.18	-> 10.192.25.47 NFS V3	COMMIT	eply (Call In 105)
01:39:42.137001	10.192.25.47	-> 10.192.25.18 NFS V3	SETATTR	Call, FH:0xe53f81da
01:39:42.141261	10.192.25.18	-> 10.192.25.47 NFS V3	SETATTR	Reply (Call In 107)

Workload Identification

ACCESS
ACCESS
LOOKUP
LOOKUP
LOOKUP
LOOKUP
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....
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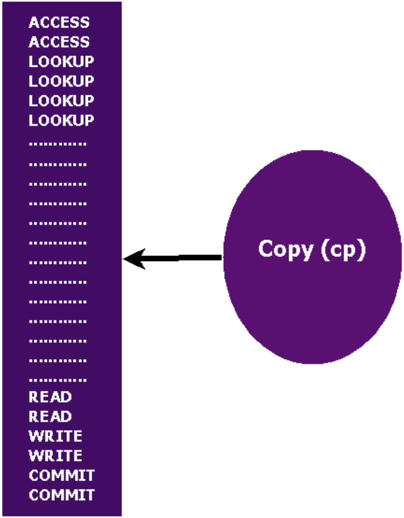
READ
READ
WRITE
WRITE
COMMIT
COMMIT

Workload Identification



Trace Annotation

```
ACCESS
ACCESS
LOOKUP
LOOKUP
...........
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...........
...........
...........
...........
...........
...........
...........
READ
WRITE
WRITE
COMMIT
COMMIT
ACCESS
ACCESS
LOOKUP
...........
...........
...........
...........
GETATTR
ACCESS
ACCESS
READ
READ
```
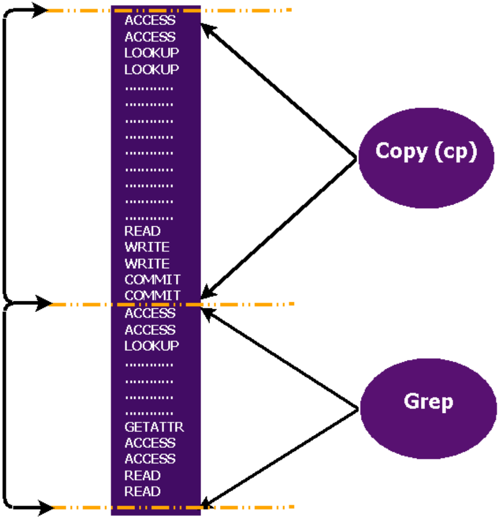

Trace Annotation



Challenges

- Variability in the traces of the same workload

cp contacts.csv con.csv

```
ACCESS Call, FH:0xe003db8b
LOOKUP Call, DH:0xe003db8b/con.csv
LOOKUP Reply Error:NFS3ERR_NOENT
LOOKUP Call, DH:0xe003db8b/contacts.csv
LOOKUP Reply, FH:0x71d9fc7c
GETATTR Call, FH:0x71d9fc7c
ACCESS Call, FH:0x71d9fc7c
CREATE Call, DH:0xe003db8b/con.csv
SETATTR Call, FH:0x58d9d57c
GETACL Call
GETATTR Call, FH:0x58d9d57c
READ Call, FH:0x71d9fc7c ...
WRITE Call, FH:0x58d9d57c ...

COMMIT Call, FH:0x58d9d57c
```

cp contacts.csv dir/con.csv

```
LOOKUP Call, DH:0xe003db8b/dir
LOOKUP Reply, FH:0x0eb18814
ACCESS Call, FH:0x0eb18814
LOOKUP Call, DH:0x0eb18814/con.csv
LOOKUP Reply Error:NFS3ERR_NOENT
LOOKUP Call, DH:0xe003db8b/contacts.csv
LOOKUP Reply, FH:0x71d9fc7c
GETATTR Call, FH:0x71d9fc7c
ACCESS Call, FH:0x71d9fc7c
CREATE Call, DH:0x0eb18814/con.csv
SETATTR Call, FH:0x14b19214
GETACL Call
GETATTR Call, FH:0x14b19214
READ Call, FH:0x71d9fc7c ...
WRITE Call, FH:0x14b19214 ...

COMMIT Call, FH:0x14b19214
```

Key Contributions

- Identifying workloads from NFS opcodes
- Identifying transitions between workloads in a trace sequence
- Small snippets of traces are sufficient!
- Exploited the analogy with Biological sequence analysis problem
- Use of Profile Hidden Markov Models(Profile HMMs)

Analogy with Problem in Computational Biology

Unfortunately,

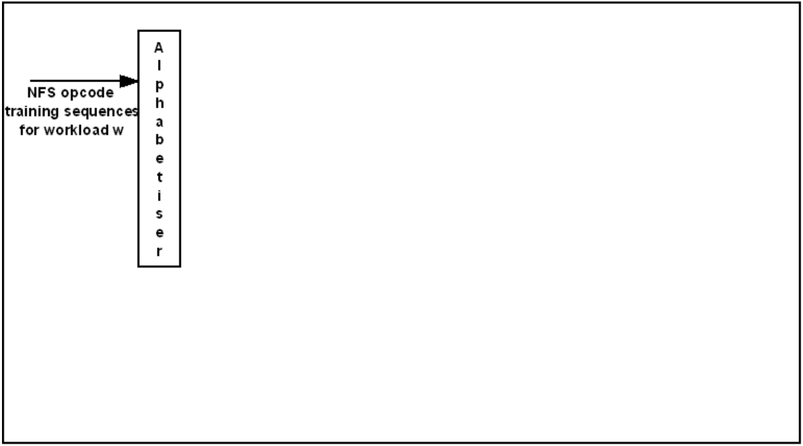
DP formulations for aligning r sequences, each of length n are expensive, $O(n^r)$, time and space complexity

Computational Biology	***Problem at Hand***
Conserved in critical regions	Similarity to a large extent
Diverge due to chance mutations	Additions, deletions and replacements of symbols observed

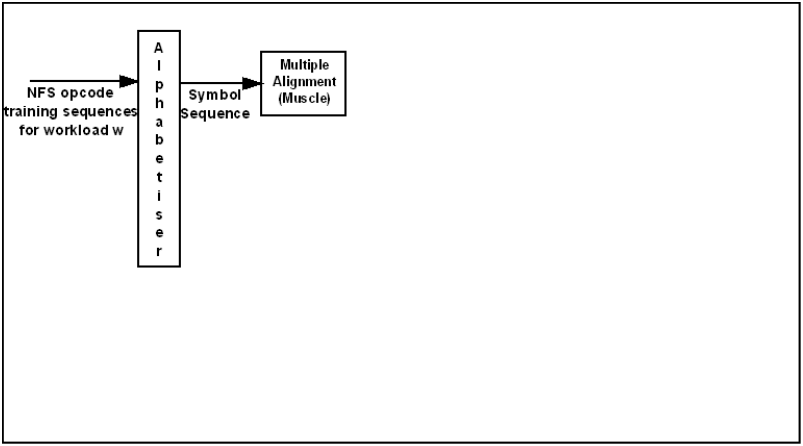
Proposal

To use Profile HMM for representing Profile of a workload

Profile HMMs Training and Usage Workflow: An Overview



Profile HMMs Training and Usage Workflow: An Overview



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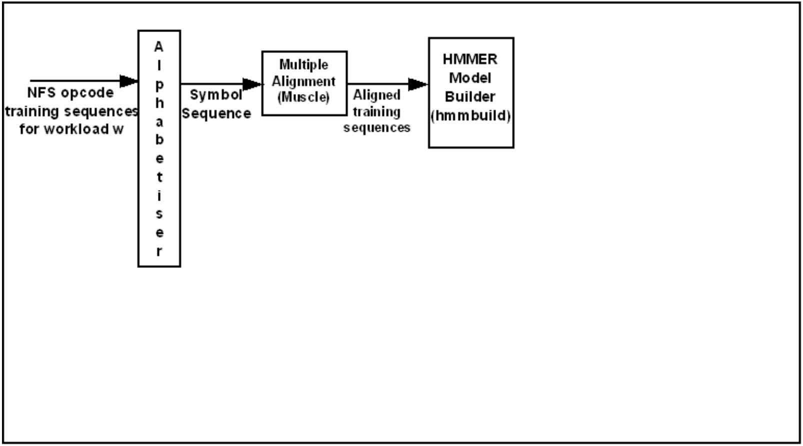

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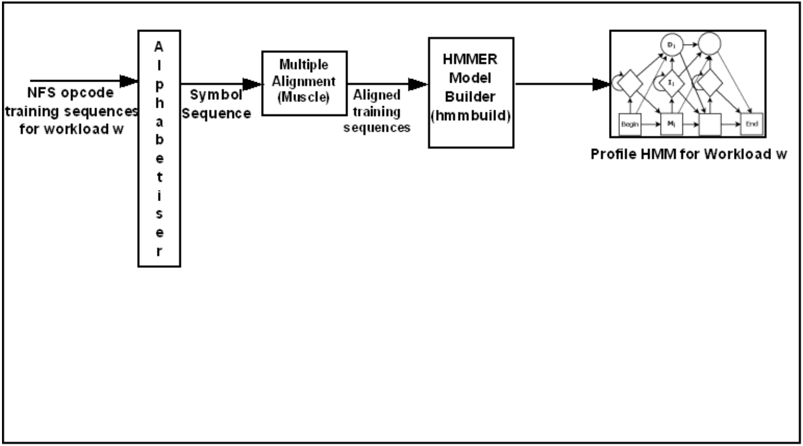

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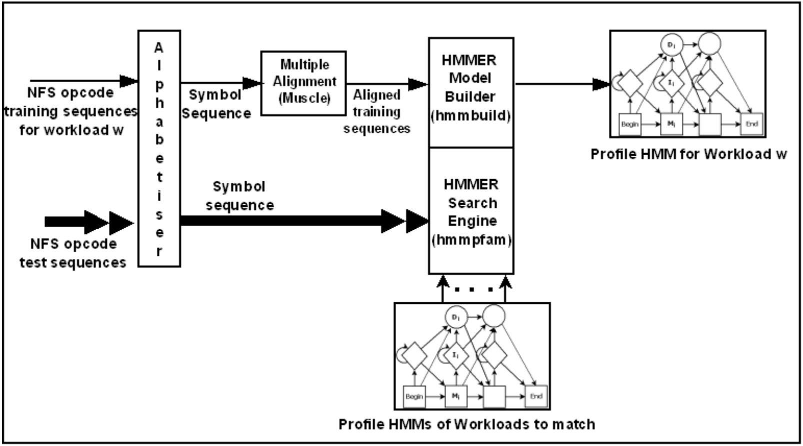
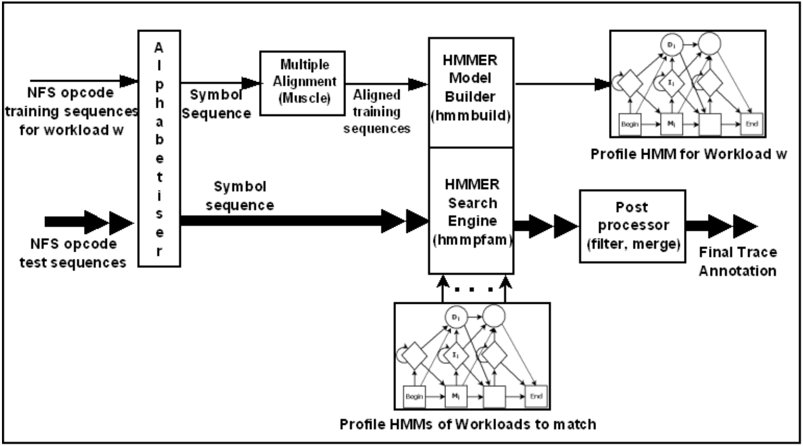


Profile HMMs Training and Usage Workflow: An Overview



Experimental Set-up

- Unix Commands
  - tar, untar, make, edit, copy, move, grep, find, compile
  - Accessing a subset of 14361 files and 1529 directories up to 7 levels deep
- TPC-C
  - 1 to 5 warehouses with 1 to 5 database clients per warehouse
- Postmark
  - a workload approximating a large internet email server

Experimental Results

Workload Identification Confusion Matrix

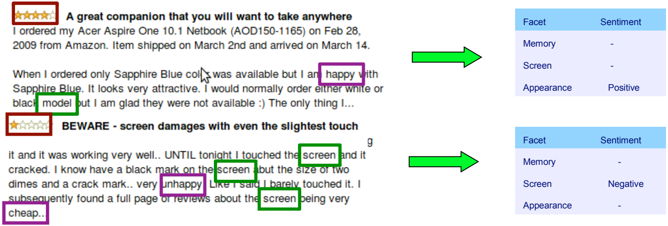
Trace Command	Models								
	make	find	grep	tar	untar	copy	move	edit	tpcc
make	91.7	1.2		1.2	2.4	3.6			
find		91.8	2.1			3.1	1		2.1
grep	1.3	1.3	85	1.3	11.3				
tar				100					
untar				1.2	98.8				
copy		1	1		6	82	1	9	
move		5.6	0.8	0.8		2.4	89.6	0.8	
edit								100	
tpcc									100

Opinion mining

Best paper award

Exploiting Coherence in Reviews for Discovering Latent Facets and associated Sentiments
Himabindu L., Bhattacharyya C., Bhattacharya I., Merugu Srujana.
Siam Data Mining Conference 2011

Mining Customer Reviews



- Central Problem: Facet based sentiment analysis of customer reviews
- Applications
  - E-commerce : product recommendation for customers
  - Business Analytics : aiding product managers and decision makers in understanding the product's market standing

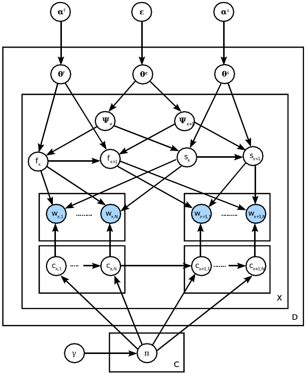
FACeT Sentiment extraction model (FACTS)

The pictures i took during my last trip with this camera were absolutely great. The picture quality is amazing and the pics come out clear and sharp. I am also very impressed with its battery life, unlike other cameras available in the market, the charge lasts long enough. However, I am unhappy with the accessories.

- FACTS aims at extracting both facets as well as associated sentiments from customer reviews
- Captures both the syntactic and semantic dependencies
- Loosely based on HMM LDA
- Facet and Sentiment classes comprise of topics

FACTS Model

Extends HMM-LDA to include topics within another syntactic class for sentiments



Choose $\theta_d^f \sim Dir(\alpha^f)$
Choose $\theta_d^s \sim Dir(\alpha^s)$
Choose $\theta_d^\epsilon \sim Dir(\epsilon)$
For each window $x \in \{1 \ldots X_d\}$
  a. Choose $\psi_{d,x} \sim Mult(\theta_d^\epsilon)$
  b. if ($\psi_{d,x}$=0)
    Choose $f_{d,x} = f_{d,x-1}$ and $s_{d,x} = s_{d,x-1}$
    else if ($\psi_{d,x}$=1)
    Choose $f_{d,x} \sim \theta_d^f$ and $s_{d,x} = s_{d,x-1}$
    else Choose $f_{d,x} \sim Mult(\theta_d^f)$ and $s_{d,x} \sim Mult(\theta_d^s)$
  c. For each word i in the window x
    i. Choose $c_{d,x,i} \sim Mult(\pi^{c_{d,x,i-1}})$
    ii. if $c_{d,x,i} = 1$, Choose $w_{d,x,i} \sim Mult(\phi^f_{f_{d,x}})$
      else if $c_{d,x,i} = 2$, Choose $w_{d,x,i} \sim Mult(\phi^s_{s_{d,x}})$
      else Choose $w_{d,x,i} \sim Mult(\phi^c_{c_{d,x,i}})$

$$c_{d,i} = 1 \Rightarrow \text{facet}$$

$$c_{d,i} = 2 \Rightarrow \text{sentiment}$$

Coherence based FACTS model (CFACTS)

The pictures i took during my last trip with this camera were absolutely great. The picture quality is amazing and the pics come out clear and sharp. I am also very impressed with its battery life, unlike other cameras available in the market, the charge lasts long enough. However, I am unhappy with the accessories.

- Coherence is an important aspect of user generated content
- In case of reviews, *facet* and *sentiment* coherence are usually prevalent

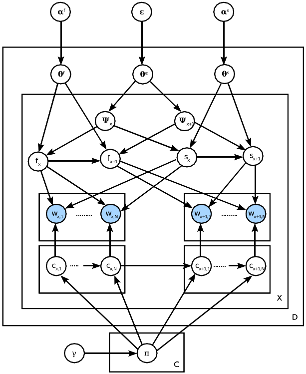
CFACTS Model

Modeling Coherence

- Each review comprises of basic units of coherence windows
- Each window is associated with a single facet and sentiment
- Continuity of topics across windows governed by parameter ψ
  - $\psi = 0 : f_{d,x} = f_{d,x-1}$ and $s_{d,x} = s_{d,x-1}$
  - $\psi = 1 : f_{d,x} = \theta_d^f$ and $s_{d,x} = s_{d,x-1}$
  - $\psi = 2 : f_{d,x} = \theta_d^f$ and $s_{d,x} = \theta_d^s$

CFACTS Model

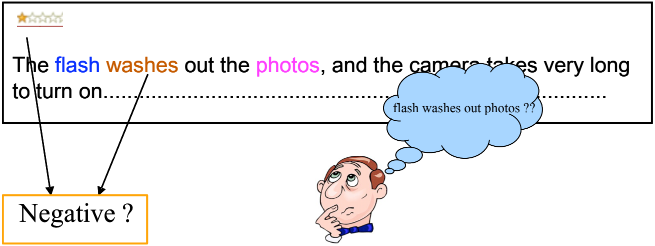
- Extends FACTS to incorporate coherence in facets/sentiments
- Also, enables loose coupling of the facet and sentiment classes



Choose $\theta_d^f \sim Dir(\alpha^f)$
Choose $\theta_d^s \sim Dir(\alpha^s)$
Choose $\theta_d^\epsilon \sim Dir(\epsilon)$
For each window $x \in \{1...X_d\}$
  a. Choose $\psi_{d,x} \sim Mult(\theta_d^\epsilon)$
  b. if ($\psi_{d,x}$=0)
    Choose $f_{d,x} = f_{d,x-1}$ and $s_{d,x} = s_{d,x-1}$
    else if ($\psi_{d,x}$=1)
    Choose $f_{d,x} \sim \theta_d^f$ and $s_{d,x} = s_{d,x-1}$
    else Choose $f_{d,x} \sim Mult(\theta_d^f)$ and $s_{d,x} \sim Mult(\theta_d^s)$
  c. For each word i in the window x
    i. Choose $c_{d,x,i} \sim Mult(\pi^{c_{d,x,i-1}})$
    ii. if $c_{d,x,i} = 1$, Choose $w_{d,x,i} \sim Mult(\phi^f_{f_{d,x}})$
      else if $c_{d,x,i} = 2$, Choose $w_{d,x,i} \sim Mult(\phi^s_{s_{d,x}})$
      else Choose $w_{d,x,i} \sim Mult(\phi^c_{c_{d,x,i}})$

Incorporating ratings - CFACTS-R

- Review ratings are valuable pointers to the sentiments expressed in reviews
- Does incorporating these review ratings help us extract sentiments better ?
  - Review ratings turn out be of immense help for ’ordering sentiment topics’



Experimental results

Qualitative Evaluation

Digital Camera Corpus

Model	Topic Label	Top Words
CFACTS-R (all topics)	Price	fit, purse, pocket, pay, worth
	Ease of use	ease, weight, casing, digicam, travel
	Picture quality	shots, video, camera, images, pics
	Accessories	charger, cable, battery, controls, button
	Display	digital, viewfinder, shots, lens, clarity
	Battery life	aa, batteries, life, ease, charge
	Portability	travel, ease, bags, portability, straps
	Features	lens, memory, point-and-shoot, software
CFACTS (all topics)	Battery life	battery, charge, shutter, aa batteries, alkaline
	Accessories	charger, camera, cable, tripod, shutter button
	Picture quality	images, clarity, camera, brightness, focus
	Features	zoom, nikon, face recognition, redeye, memory
	Ease of use	ease, use, design, color, grip
	Display	slr, lcd, viewfinder, display, point-and-shoot
	Price	price, worth, discount, warranty, fit
	Portability	ease, portability, size, lightweight, travel
FACTS-R (out of 8 topics)	Accessories	buttons, tripod, controls, batteries, purse
	Lens	shutter, minolta, camera, point-and-shoot
	Portability	range, size, weight, bag, design
	-	memory, quality, purchase, warranty, cams
	Picture quality	pictures, quality, images, resolution, sharp
FACTS (out of 8 topics)	Lens	shutter, lens, camera, point-and-shoot
	Portability	range, size, weight, bag, design
	-	pics, shots, range, ease, straps
	Picture quality	pictures, quality, images, resolution, sharp
	Accessories	buttons, controls, charger, tripod, purse
LDA (out of 9 topics)	Accessories	replace, charger, reader, digicam, easy
	-	take, shoot, carry, great, easy
	Picture quality	images, camera, pics, like, good
	-	charger, lens, awful, camera, shutter

Quantitative Evaluation

Facet Coverage - the fraction of extracted facets that actually correspond to product attributes. Benchmarked against amazon's structured ratings facets
Facet Purity – the fraction of the top words in the facet that actually correspond to the product attribute

Corpus	Model	Facet Coverage(%)	Topic Purity(%)
Digital Cameras	CFACTS-R	**100**	80.18
	CFACTS	**100**	**84**
	FACTS-R	33	74.73
	FACTS	33	72.28
	LDA	16.67	44.37
Laptops	CFACTS-R	**83.33**	**87.09**
	CFACTS	**83.33**	**87.09**
	FACTS-R	33.33	74.19
	FACTS	33.33	77.41
	LDA	33.33	45.16
Mobile Phones	CFACTS-R	**80**	**91.48**
	CFACTS	**80**	89.36
	FACTS-R	40	74.46
	FACTS	40	80.85
	LDA	40	40.42
LCD TVs	CFACTS-R	**80**	78.94
	CFACTS	**80**	**84.21**
	FACTS-R	60	68.42
	FACTS	60	65.78
	LDA	40	36.84
Printers	CFACTS-R	**100**	79.31
	CFACTS	**100**	**84.48**
	FACTS-R	75	75.86
	FACTS	75	72.41
	LDA	75	36.76

Thanks !