Extreme Classification

A New Paradigm for Ranking & Recommendation

Manik Varma
Microsoft Research

Classification

Pick one	Pick one	Pick all that apply
✓ **Label 1**	**Label 1**	✓ **Label 1**
Label 2	**Label 2**	**Label 2**
	✓ **Label 3**	✓ **Label 3**
	…	**…**
	Label *L*	**Label *L***
Binary	Multi-class	Multi-label

Extreme Multi-label Learning

- Learning with millions of labels

Predict the set of monetizable Bing queries that might lead to a click on this ad

geico auto insurance
geico car insurance
geico insurance
www geico com
care geicos
geico com
need cheap auto insurance
wisconsin cheap car insurance quotes
cheap auto insurance florida
all state car insurance coupon code

MLRF: Multi-label Random Forests [Agrawal, Gupta, Prabhu, Varma WWW 2013]

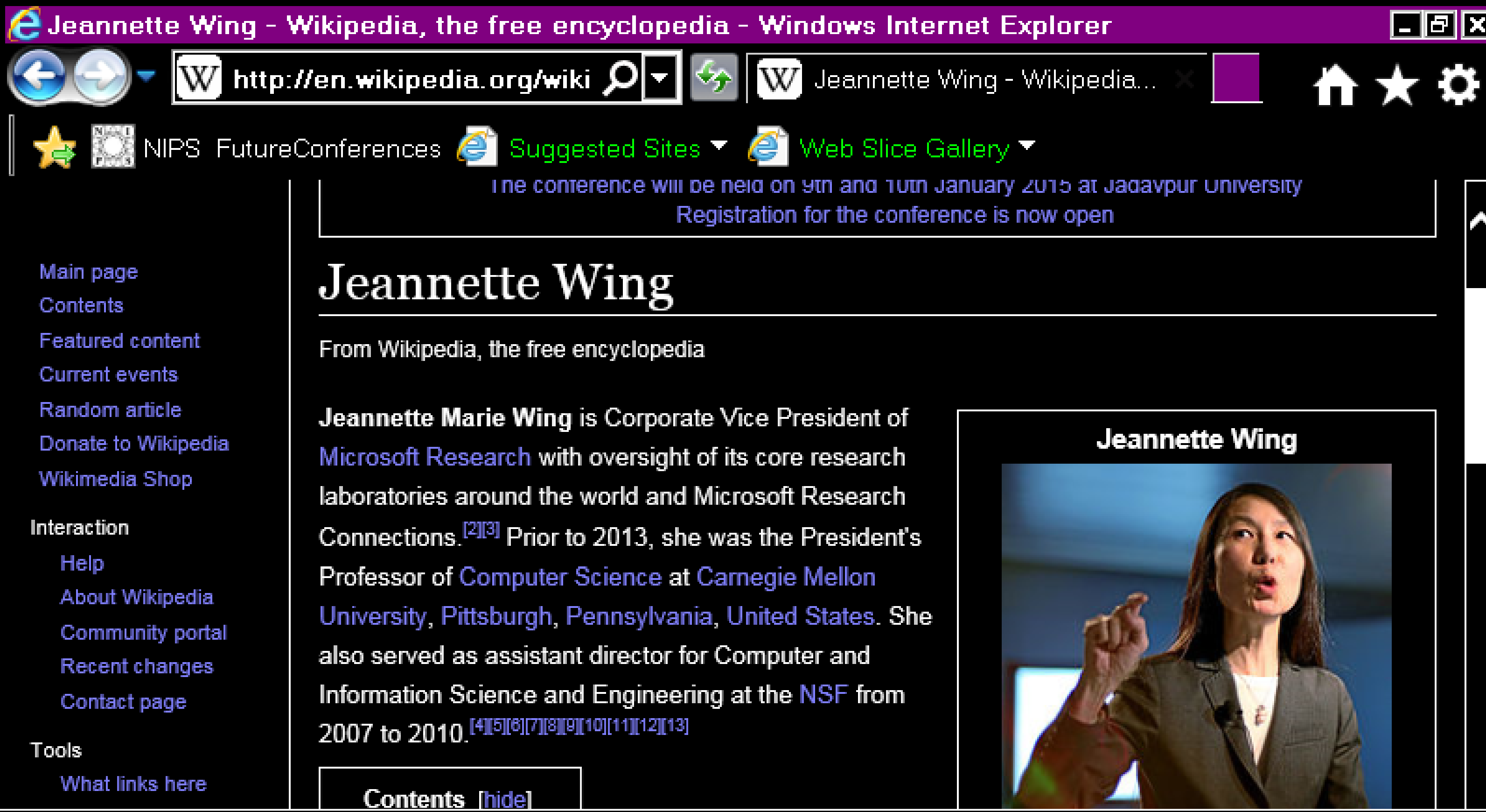
Research Problems

- Defining millions of labels
- Obtaining good quality training data
- Training using limited resources
- Log time and log space prediction
- Obtaining discriminative features at scale
- Performance evaluation
- Dealing with tail labels and label correlations
- Dealing with missing and noisy labels
- Statistical guarantees
- Applications

Extreme Multi-label Learning - People

- Which people are present in this selfie?

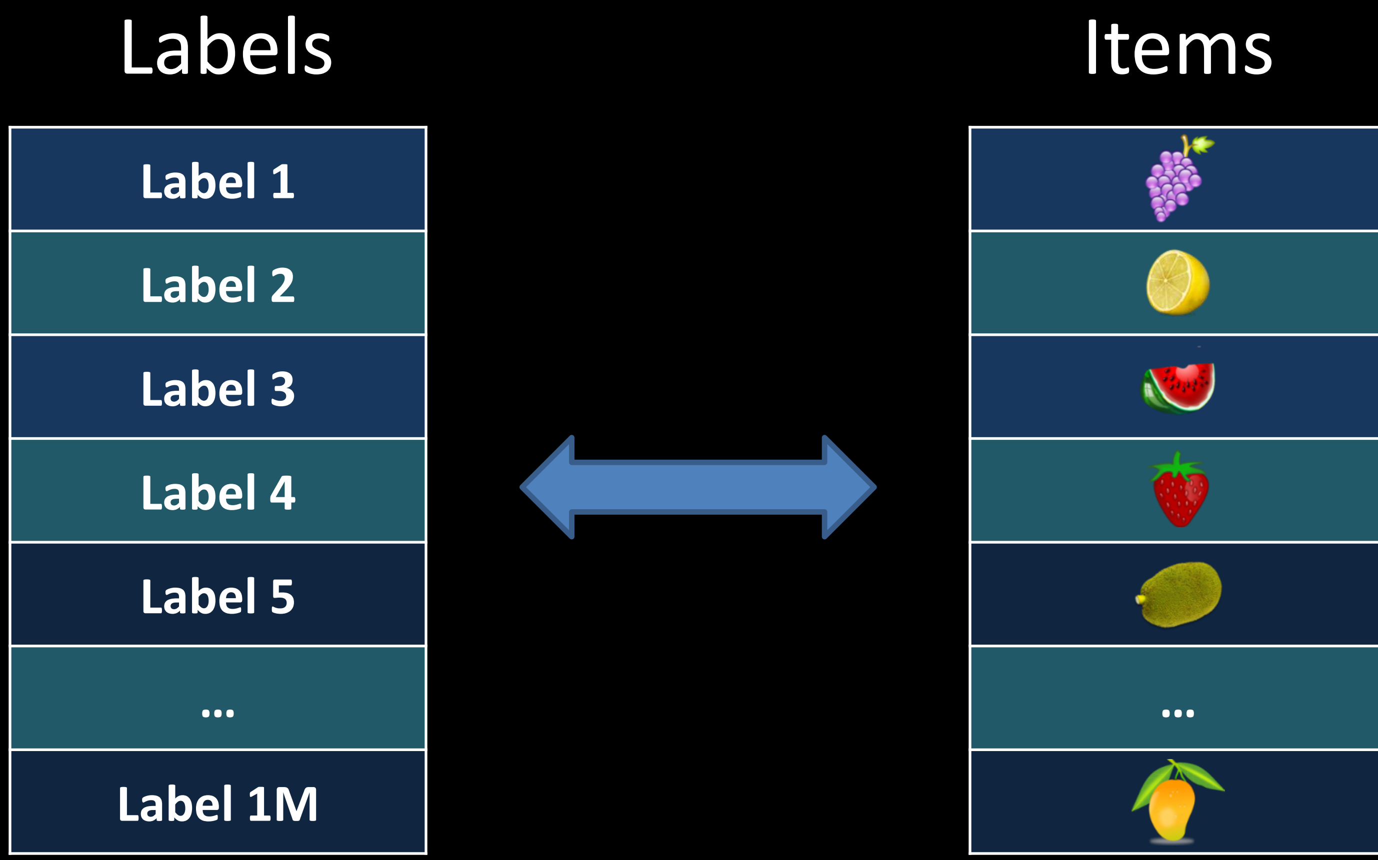
Extreme Multi-label Learning – Wikipedia



Labels: Living people, American computer scientists, Formal methods people, Carnegie Mellon University faculty, Massachusetts Institute of Technology alumni, Academic journal editors, Women in technology, Women computer scientists.

Reformulating ML Problems

- Ranking or recommending millions of items



FastXML

A Fast, Accurate & Stable Tree-classifier for eXtreme Multi-label Learning

Yashoteja Prabhu (IIT Delhi)
Manik Varma (Microsoft Research)

FastXML

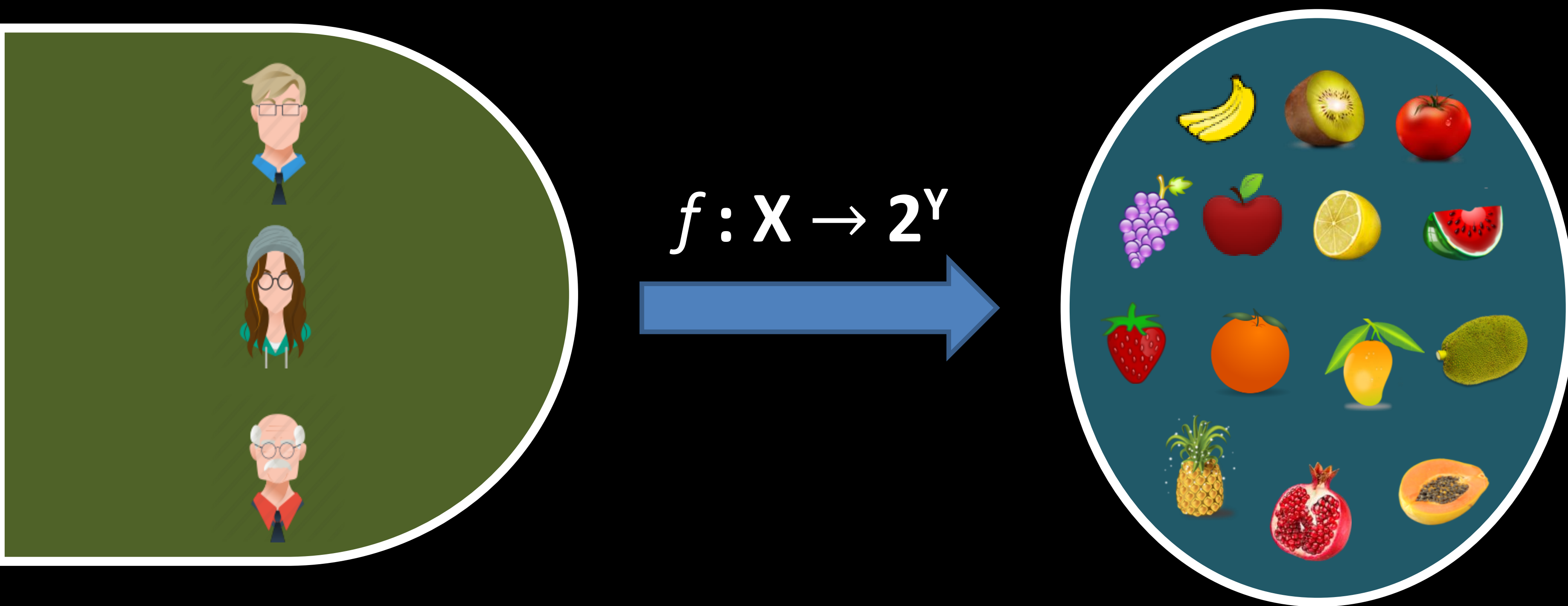
- Logarithmic time prediction in milliseconds
  - Ensemble of balanced tree classifiers

- Accuracy gains upto 25% over competing methods
  - Nodes partitioned using nDCG

- Upto 1000x faster training over the state-of-the-art
  - Alternating minimization based optimization
  - Proof of convergence to a stationary point

Extreme Multi-Label Learning

- Problem formulation

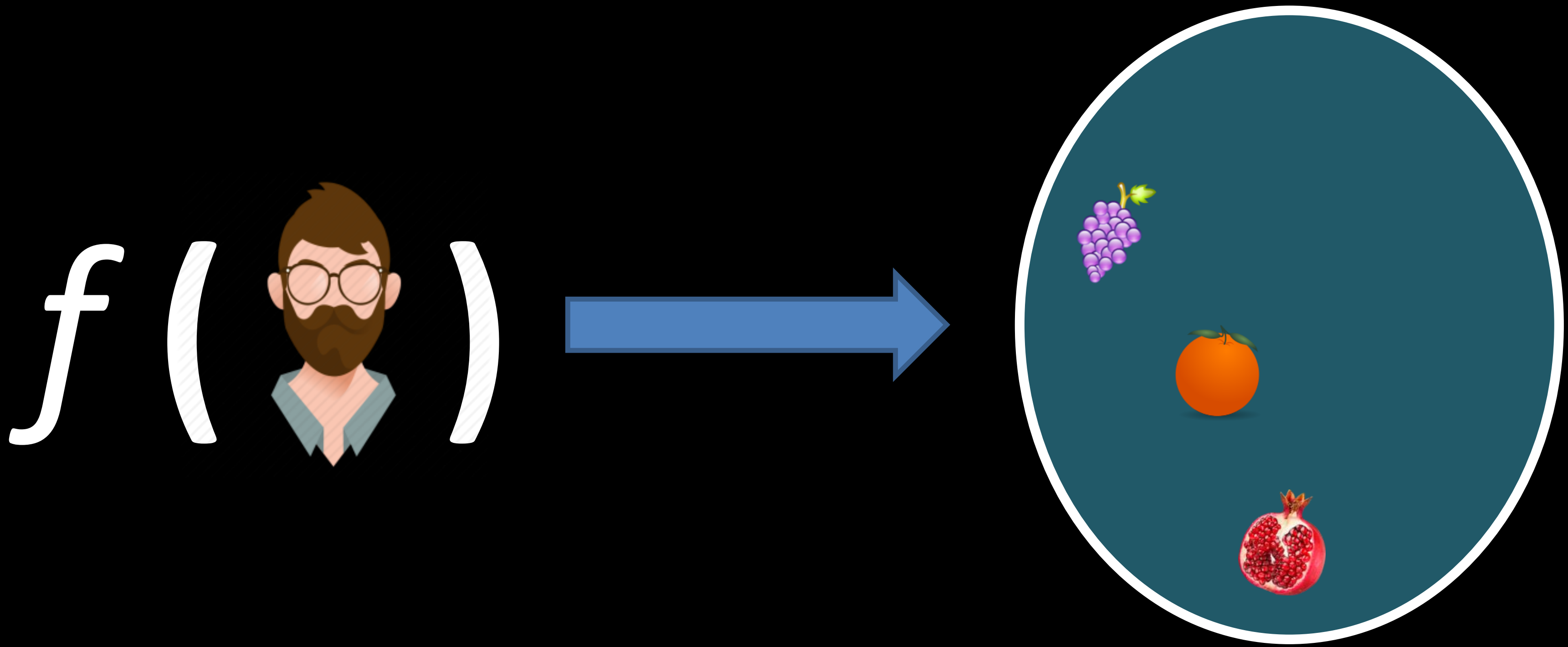


X: Users

Y: Items

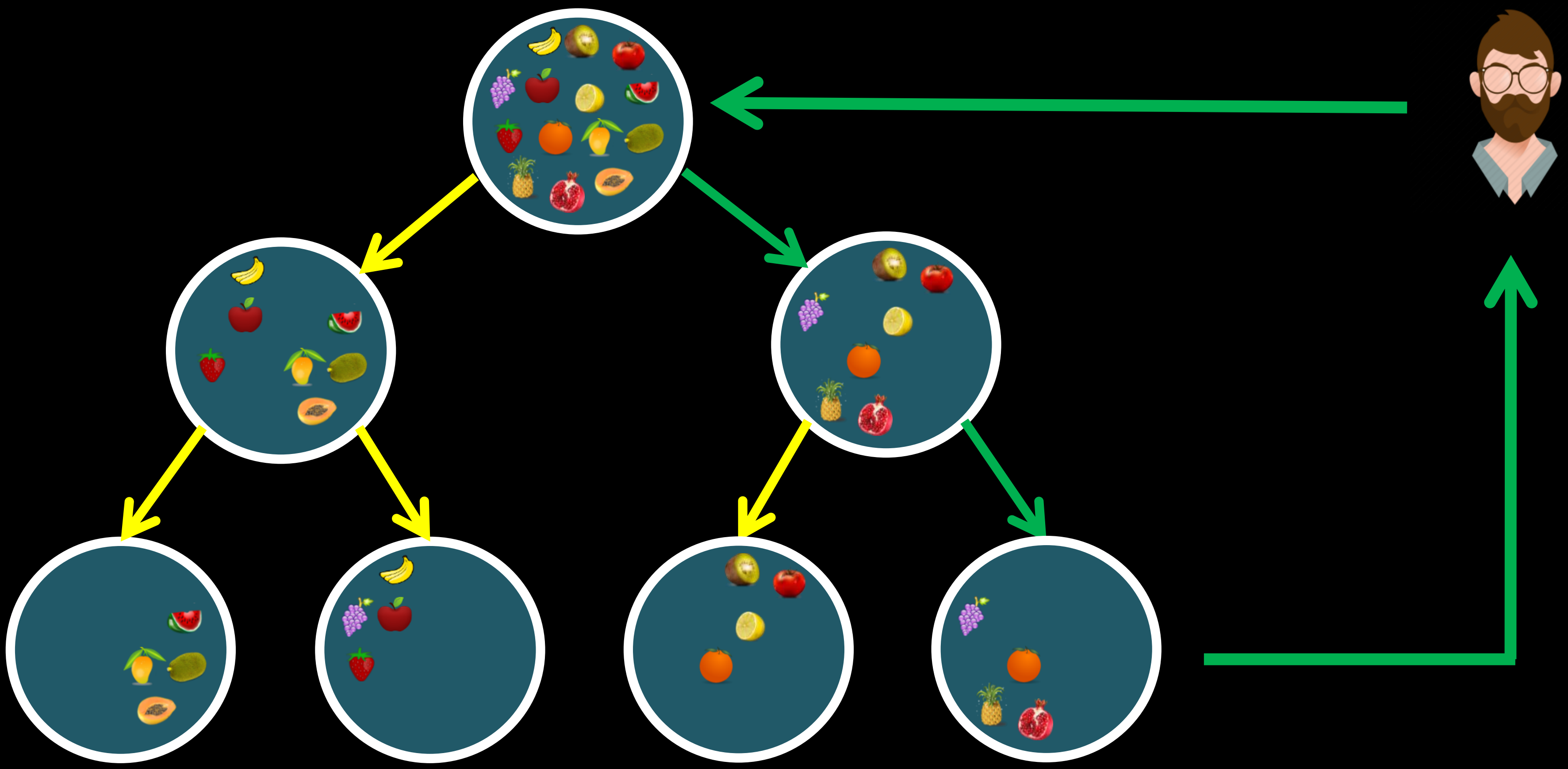
Extreme Multi-Label Learning

- Problem formulation



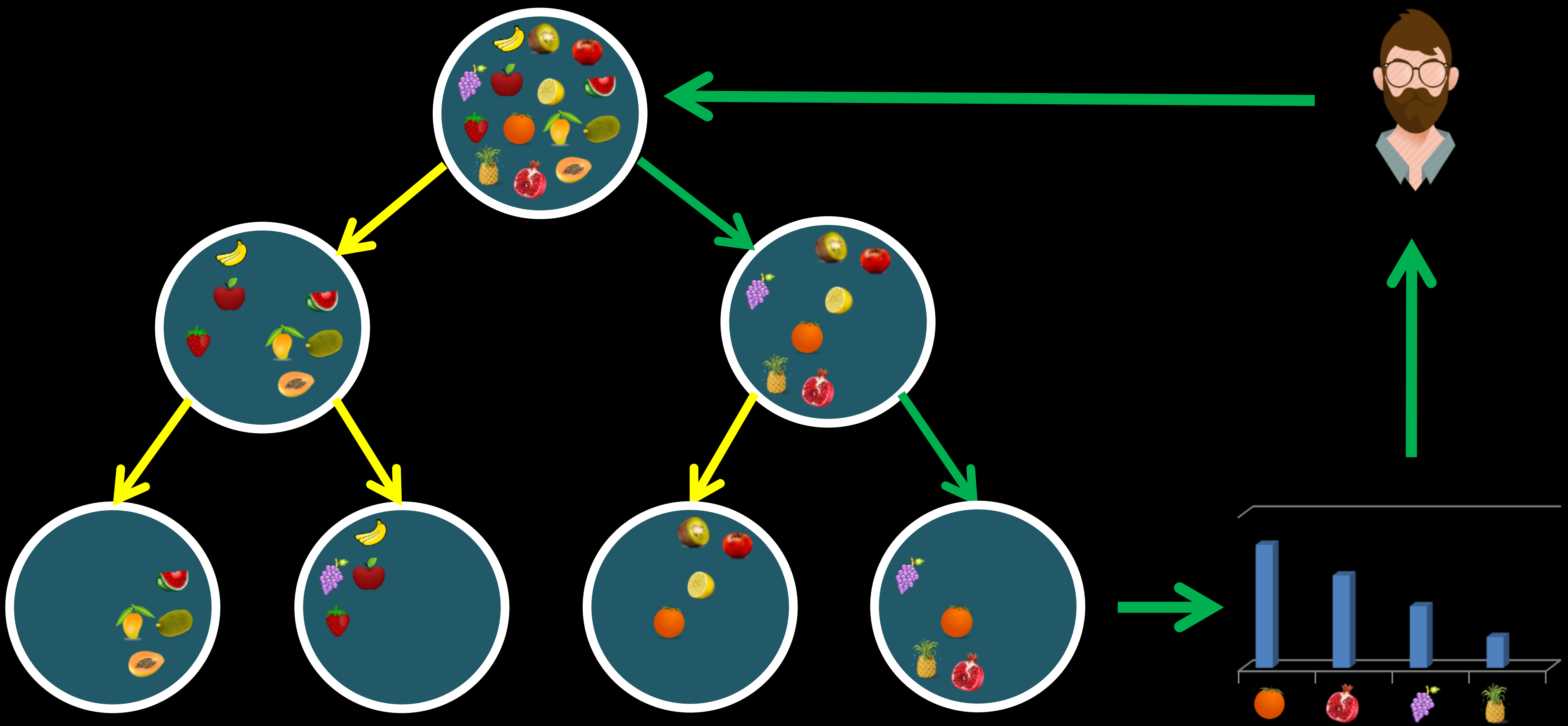
Tree Based Extreme Classification

- Prediction in logarithmic time

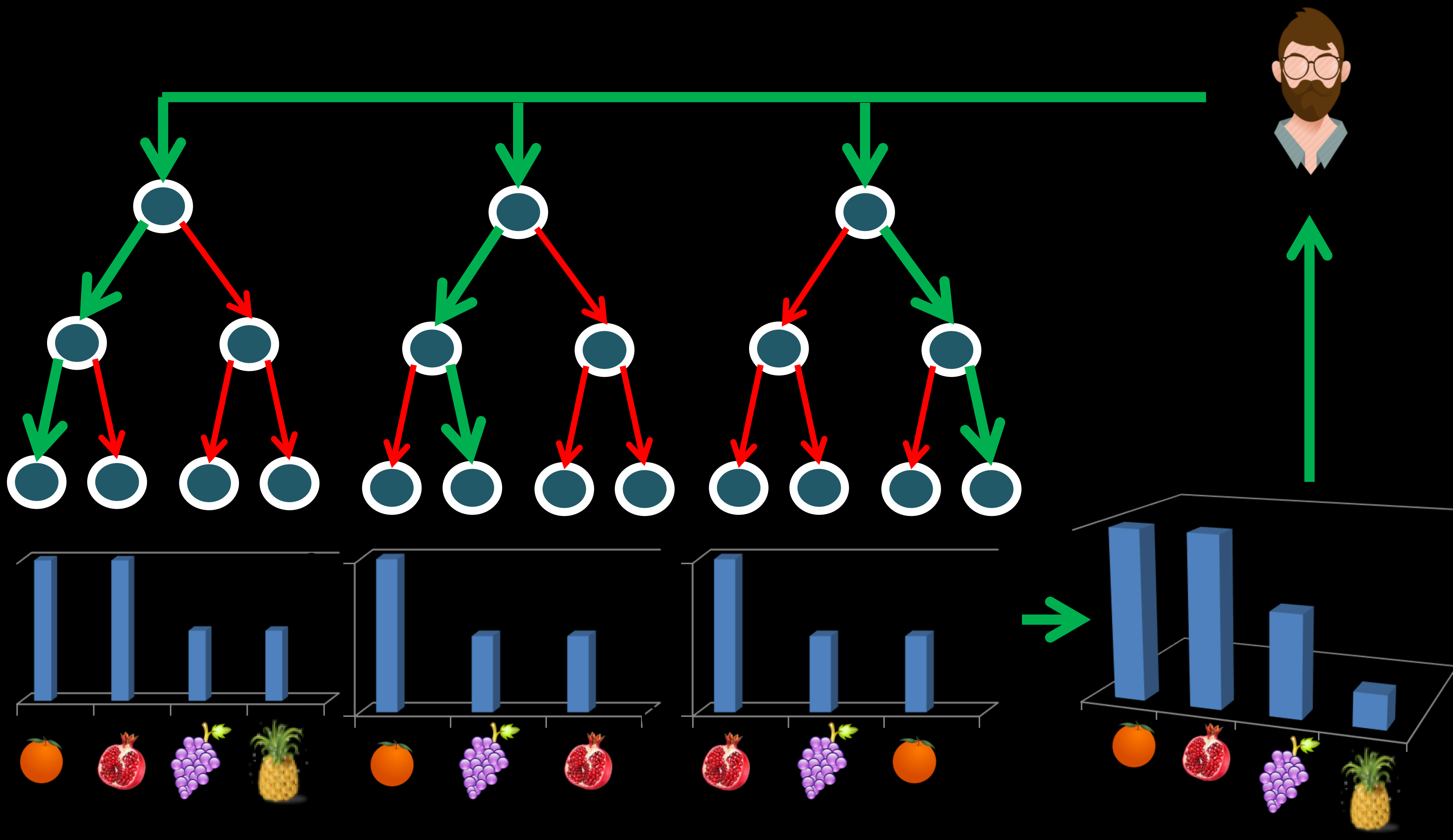


Tree Based Extreme Classification

- Prediction in logarithmic time



FastXML Architecture



FastXML

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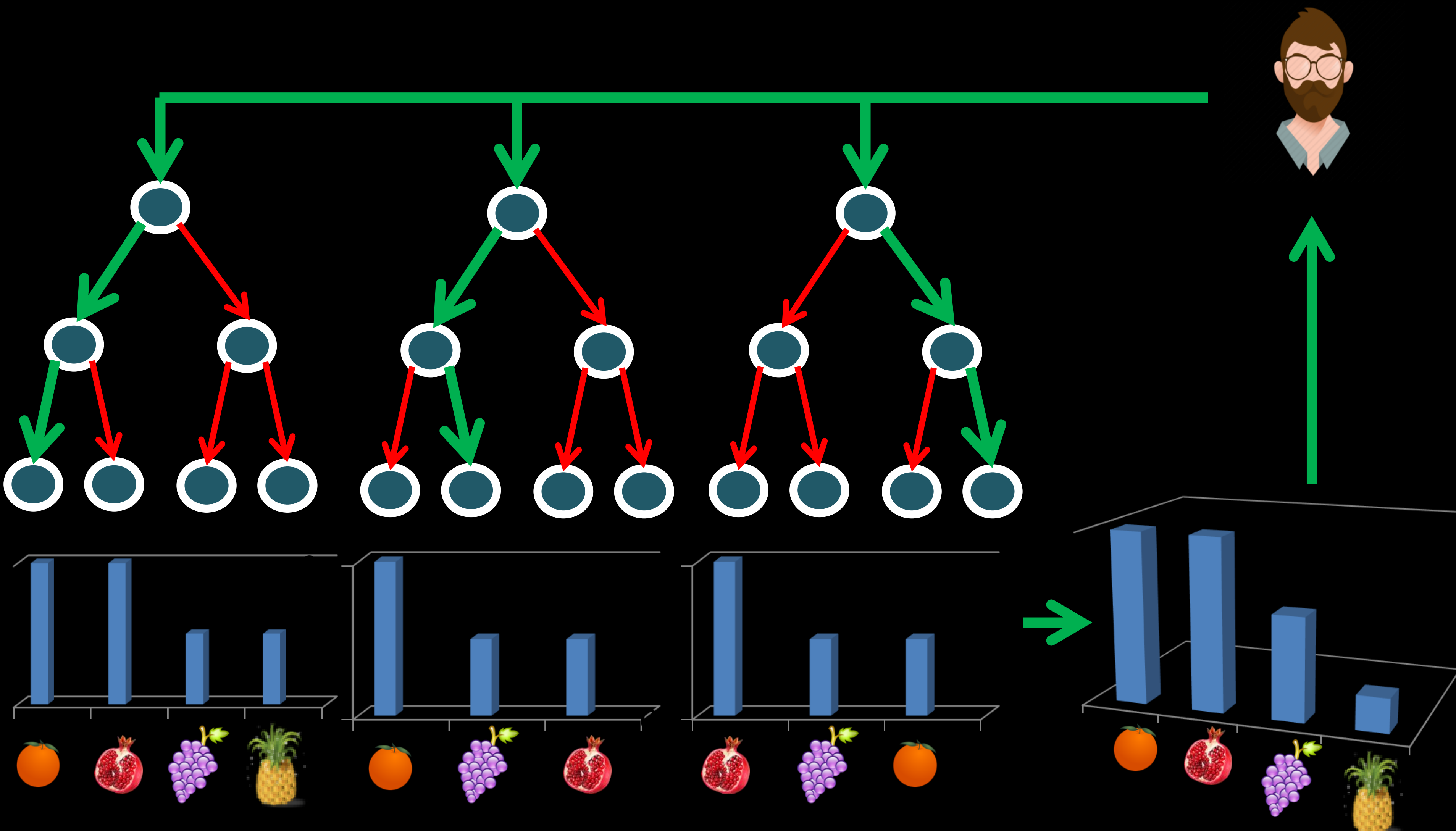
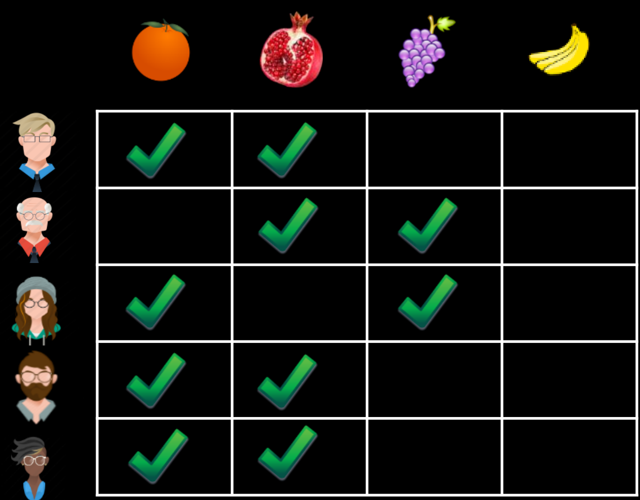
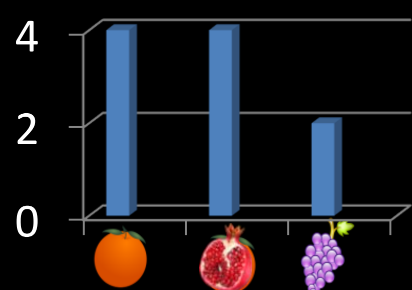
FastXML Architecture

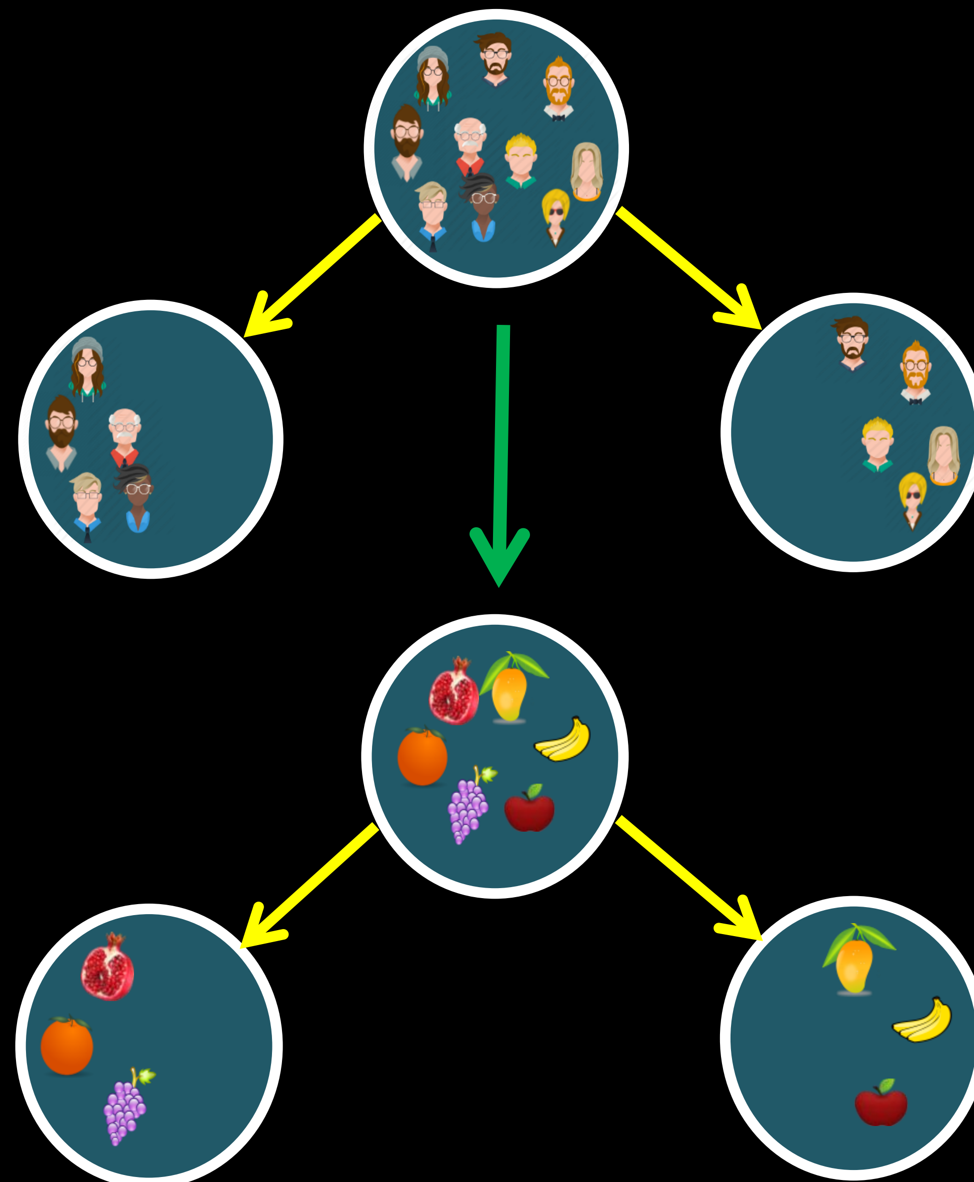


Learning to Partition a Node

Training data

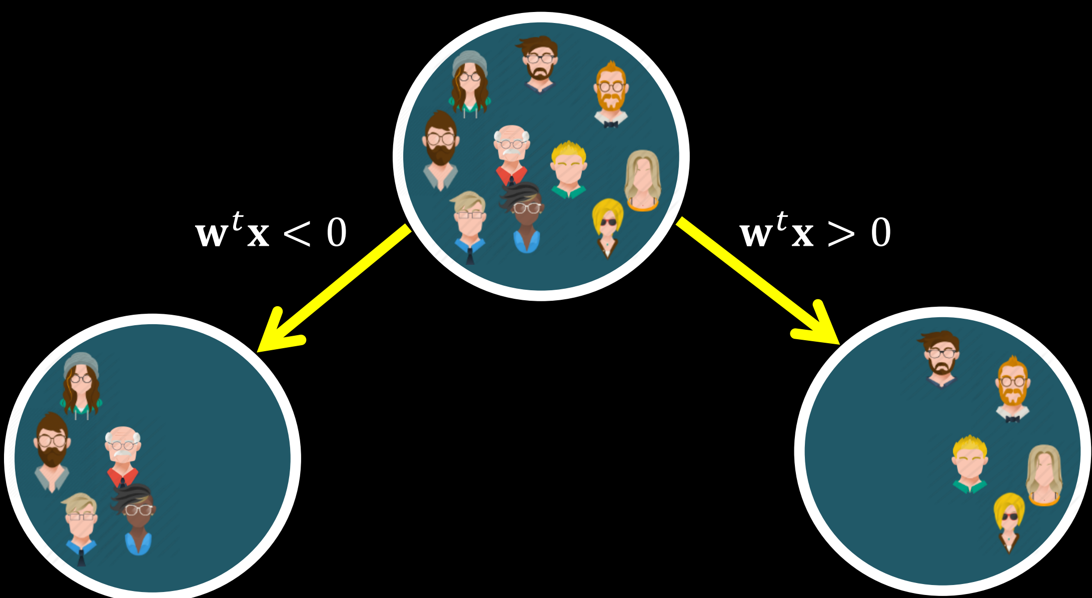


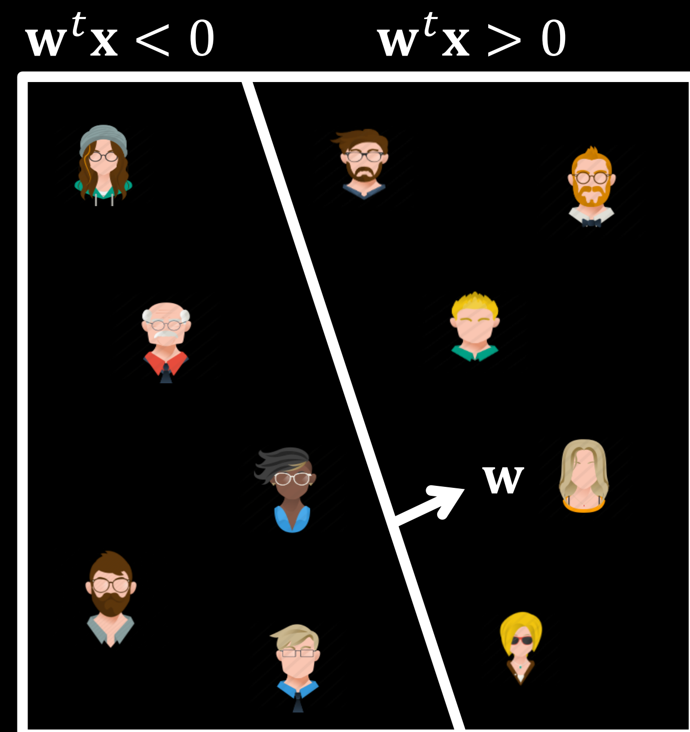




Learning to Partition a Node

$$\mathrm{Min}_{\mathbf{w}} \quad \|\mathbf{w}\|_1 - C \sum_{i \in \mathrm{Users}} \mathrm{nDCG}\,(\mathbf{x}_i, \mathbf{y}_i, \mathbf{w})$$





X: Space of Users

FastXML

- Logarithmic time prediction in milliseconds
  - Ensemble of balanced tree classifiers

- Accuracy gains upto 25% over competing methods
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- Upto 1000x faster training over the state-of-the-art
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Optimizing nDCG

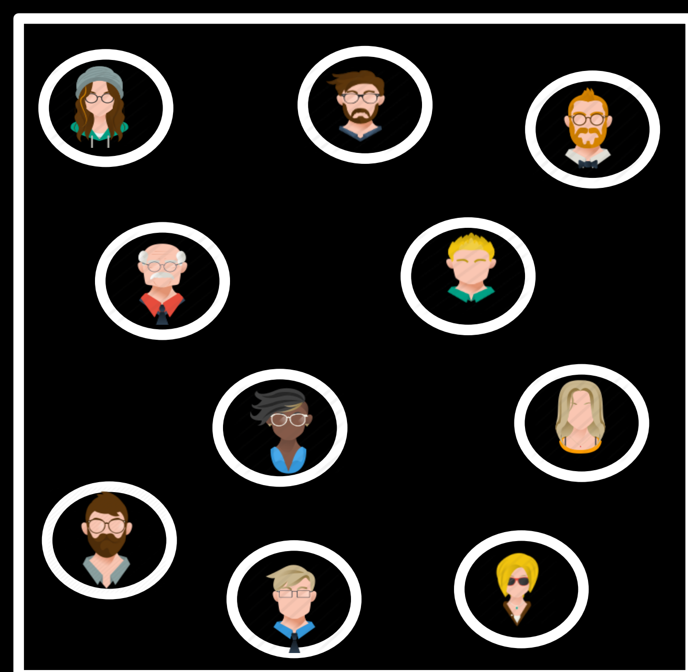
- nDCG is hard to optimize
  - nDCG is non-convex and non-smooth
  - Large input variations → No change in nDCG
  - Small input variations → Large changes in nDCG

$$\mathrm{nDCG} \propto \mathrm{like}(i, \mathbf{r}_1) + \sum_{l=2}^{L} \frac{\mathrm{like}(i, \mathbf{r}_l)}{\log(l+1)}$$

$$\mathrm{like}(i, \mathbf{r}_l) = \begin{cases} 1 \text{ If user } i \text{ likes the item with rank } \mathbf{r}_l \\ 0 \text{ otherwise} \end{cases}$$

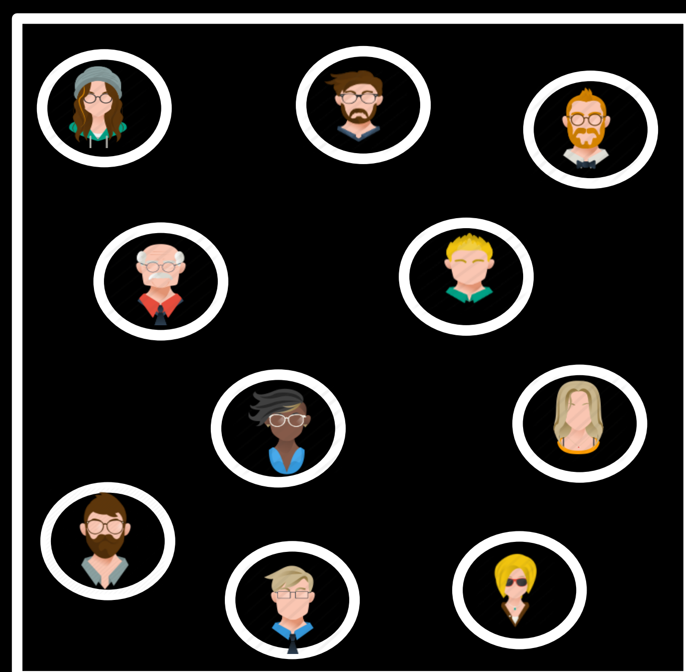
Optimizing nDCG

$$\text{Min}_{\mathbf{w}} \quad \|\mathbf{w}\|_1 - C \sum_{i \in \text{Users}} \text{nDCG}\left(\mathbf{x}_i, \mathbf{y}_i, \mathbf{w}\right)$$



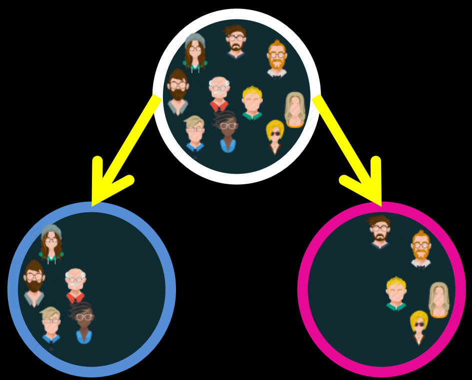
Optimizing nDCG – Reformulation

$$\mathrm{Min}_{\mathbf{w},\boldsymbol{\delta},\mathbf{r}^{\pm}} \quad \|\mathbf{w}\|_1 + \sum_i C_\delta(\delta_i)\log\left(1+e^{-\delta_i \mathbf{w}^t \mathbf{x}_i}\right) - C_r \sum_i \mathrm{nDCG}\left(\mathbf{r}^{\delta_i}\right)^t N_{\mathbf{y}_i}\,\mathbf{y}_i$$

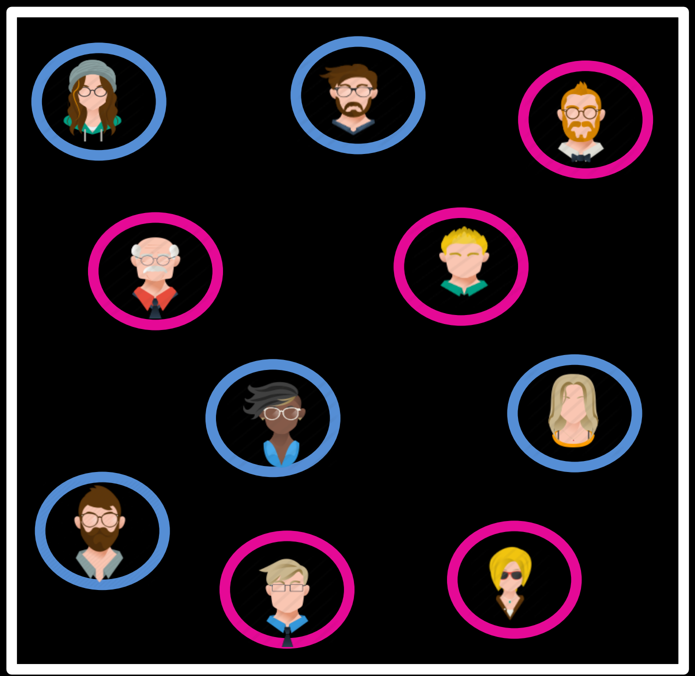


Optimizing nDCG – Initialization

$$\mathrm{Min}_{\mathbf{w},\boldsymbol{\delta},\mathbf{r}^{\pm}} \;\; \|\mathbf{w}\|_1 + \sum_i C_\delta(\delta_i) \log\left(1 + e^{-\delta_i \mathbf{w}^t \mathbf{x}_i}\right) - C_r \sum_i \mathrm{nDCG}\left(\mathbf{r}^{\delta_i}\right)^t N_{\mathbf{y}_i} \mathbf{y}_i$$



$$\delta_i \;\; \sim \mathrm{Bernoulli}(0.5), \forall i$$



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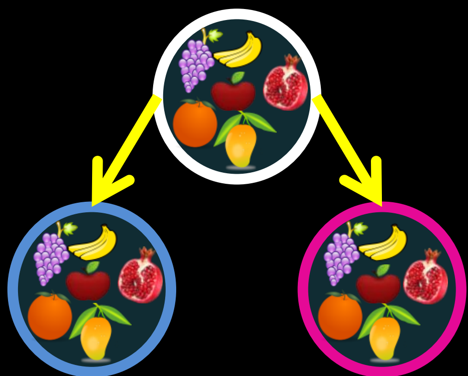

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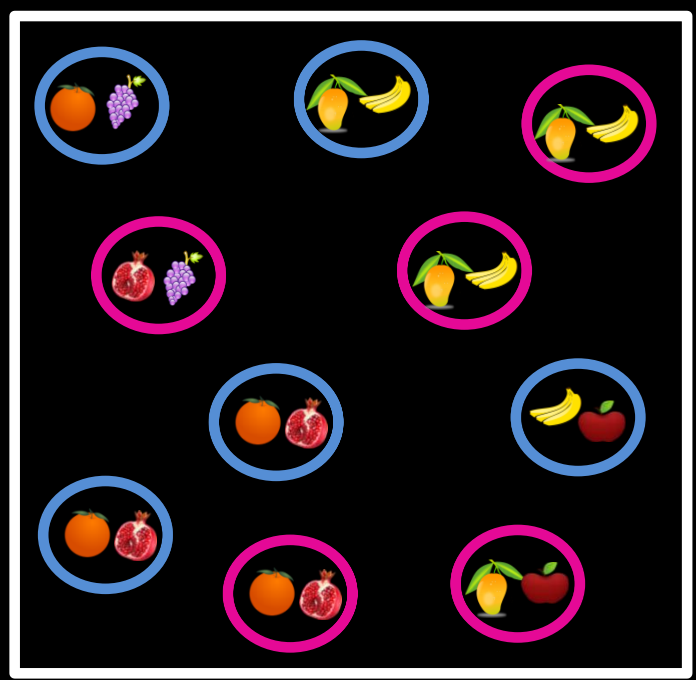
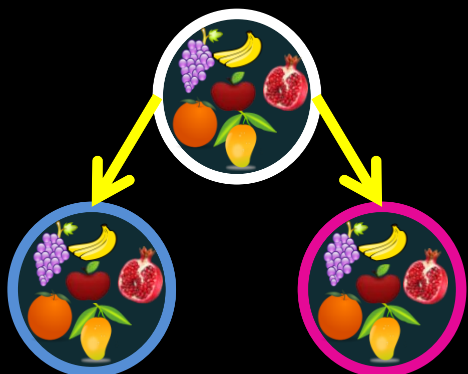
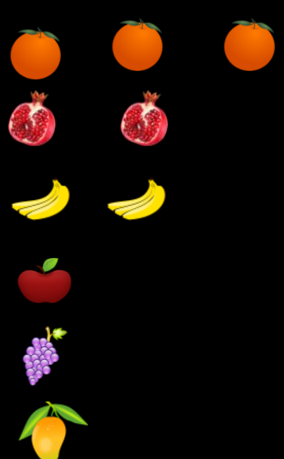


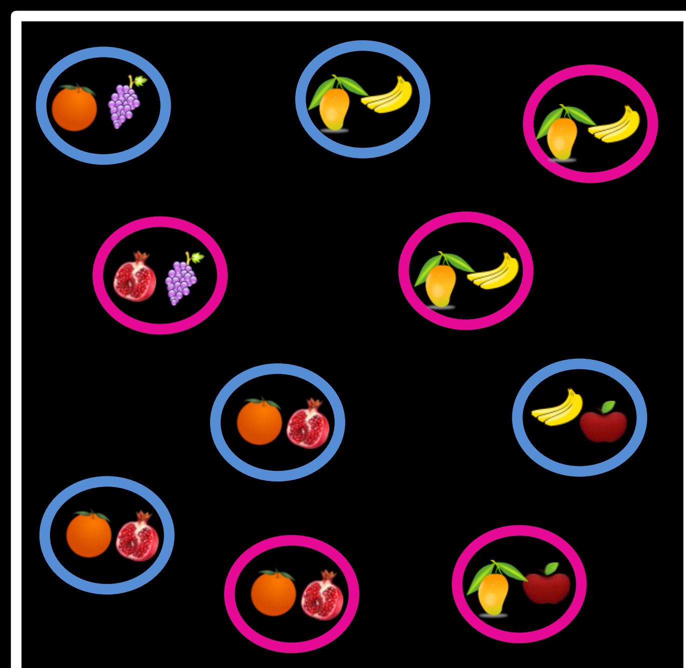
Optimizing nDCG – Initialization

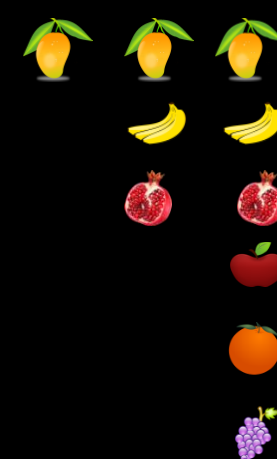
$$\text{Min}_{\mathbf{w},\boldsymbol{\delta},\mathbf{r}^{\pm}} \; \|\mathbf{w}\|_1 + \sum_i C_\delta(\delta_i) \log\left(1 + e^{-\delta_i \mathbf{w}^t \mathbf{x}_i}\right) - C_r \sum_i \text{nDCG}\left(\mathbf{r}^{\delta_i}\right)^t N_{\mathbf{y}_i} \mathbf{y}_i$$



$$\mathbf{r}^{\pm *} = \text{rank}\left(\sum_{i:\, \delta_i = \pm 1} N_{\mathbf{y}_i} \mathbf{y}_i\right)$$

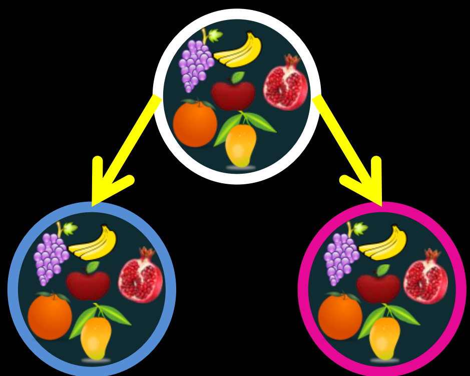






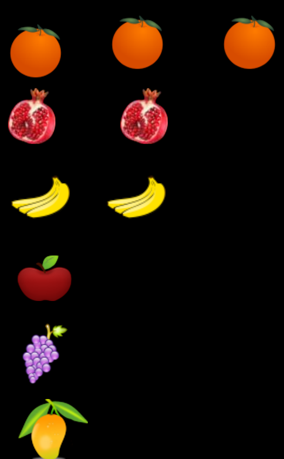
Optimizing nDCG – Repartitioning Users

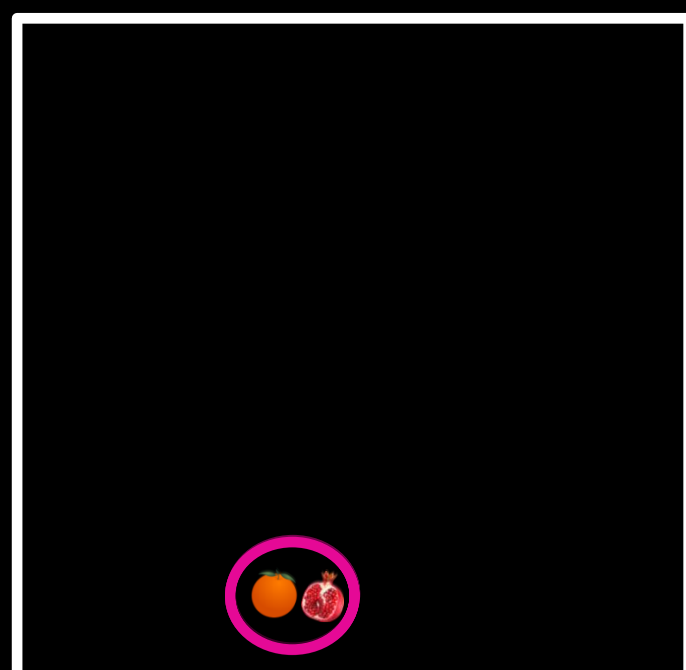
$$\mathrm{Min}_{\mathbf{w},\boldsymbol{\delta},\mathbf{r}^{\pm}} \quad \|\mathbf{w}\|_1 + \sum_i C_\delta(\delta_i) \log\left(1 + e^{-\delta_i \mathbf{w}^t \mathbf{x}_i}\right) - C_r \sum_i \mathrm{nDCG}\left(\mathbf{r}^{\delta_i}\right)^t N_{\mathbf{y}_i} \mathbf{y}_i$$

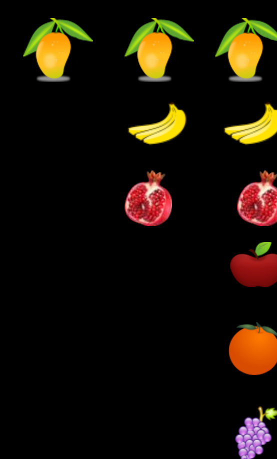


$$\delta_i^* = \mathrm{sign}\left(v_i^- - v_i^+\right)$$

$$v_i^{\pm} = C_\delta(\pm 1) \log\left(1 + e^{\mp \mathbf{w}^t \mathbf{x}_i}\right) - C_r \mathrm{nDCG}\left(\mathbf{r}^{\pm}\right)^t N_{\mathbf{y}_i} \mathbf{y}_i$$

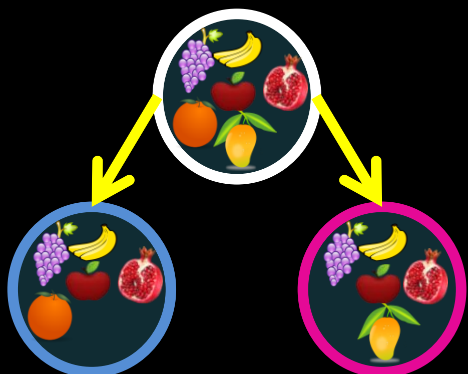






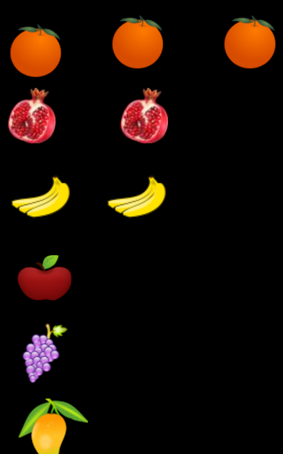
Optimizing nDCG – Repartitioning Users

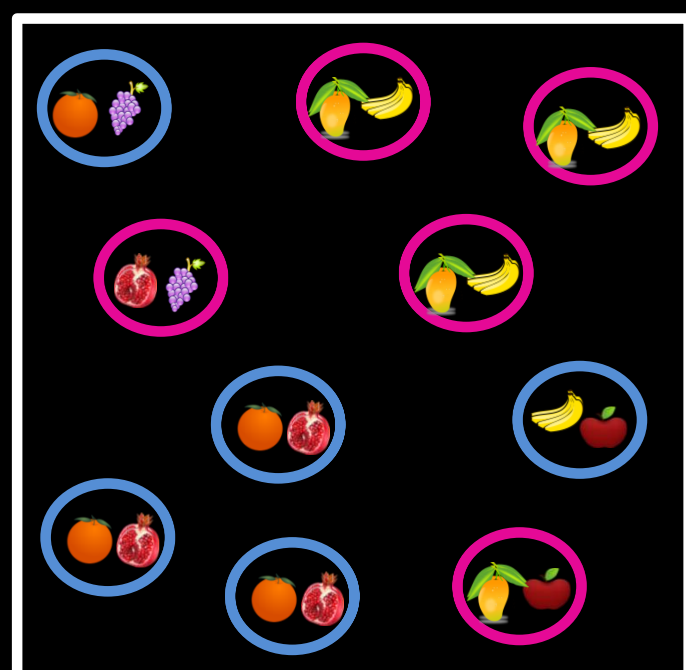
$$\mathrm{Min}_{\mathbf{w},\boldsymbol{\delta},\mathbf{r}^{\pm}} \;\; \|\mathbf{w}\|_1 + \sum_i C_\delta(\delta_i) \log\left(1 + e^{-\delta_i \mathbf{w}^t \mathbf{x}_i}\right) - C_r \sum_i \mathrm{nDCG}\left(\mathbf{r}^{\delta_i}\right)^t N_{\mathbf{y}_i} \mathbf{y}_i$$

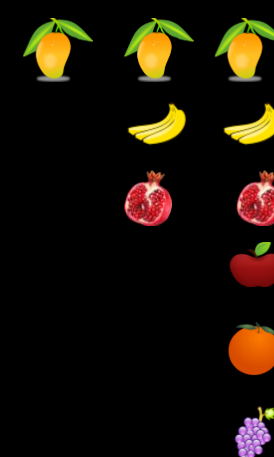


$$\delta_i^* = \mathrm{sign}\left(v_i^- - v_i^+\right)$$

$$v_i^{\pm} = C_\delta(\pm 1) \log\left(1 + e^{\mp \mathbf{w}^t \mathbf{x}_i}\right) - C_r \mathrm{nDCG}\left(\mathbf{r}^{\pm}\right)^t N_{\mathbf{y}_i} \mathbf{y}_i$$



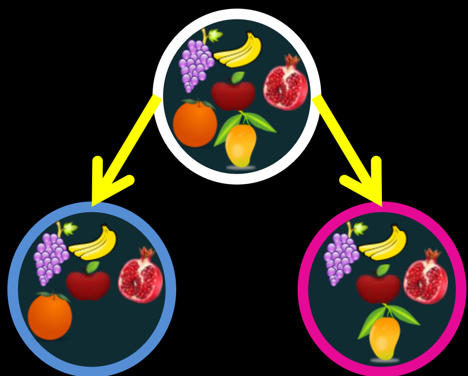


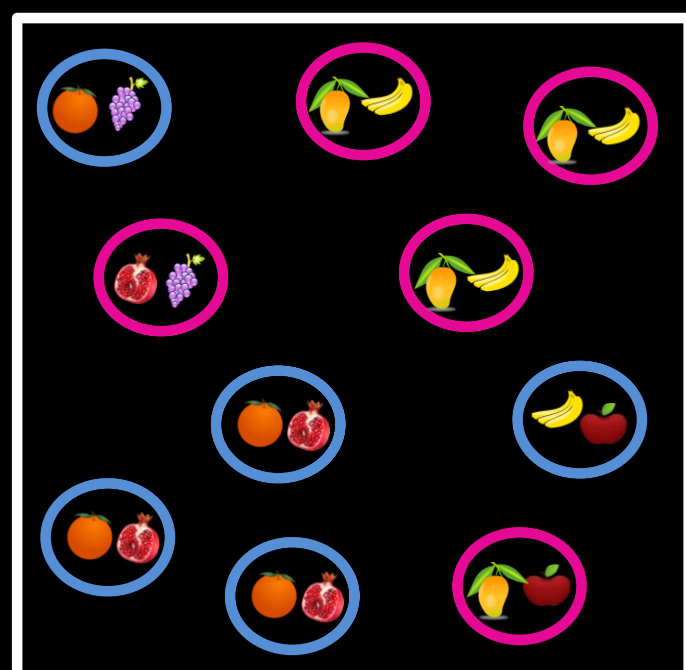


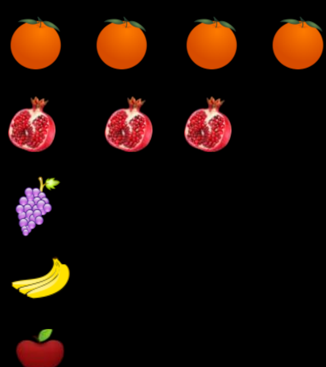
Optimizing nDCG – Reranking Items

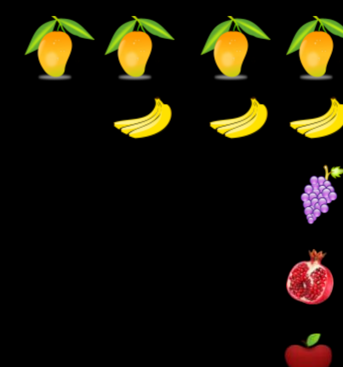
$$\mathrm{Min}_{\mathbf{w},\boldsymbol{\delta},\mathbf{r}^{\pm}} \;\; \|\mathbf{w}\|_1 + \sum_i C_\delta(\delta_i) \log\left(1 + e^{-\delta_i \mathbf{w}^t \mathbf{x}_i}\right) - C_r \sum_i \mathrm{nDCG}\left(\mathbf{r}^{\delta_i}\right)^t N_{\mathbf{y}_i} \mathbf{y}_i$$

$$\mathbf{r}^{\pm *} = \mathrm{rank}\left(\sum_{i:\, \delta_i = \pm 1} N_{\mathbf{y}_i} \mathbf{y}_i \right)$$



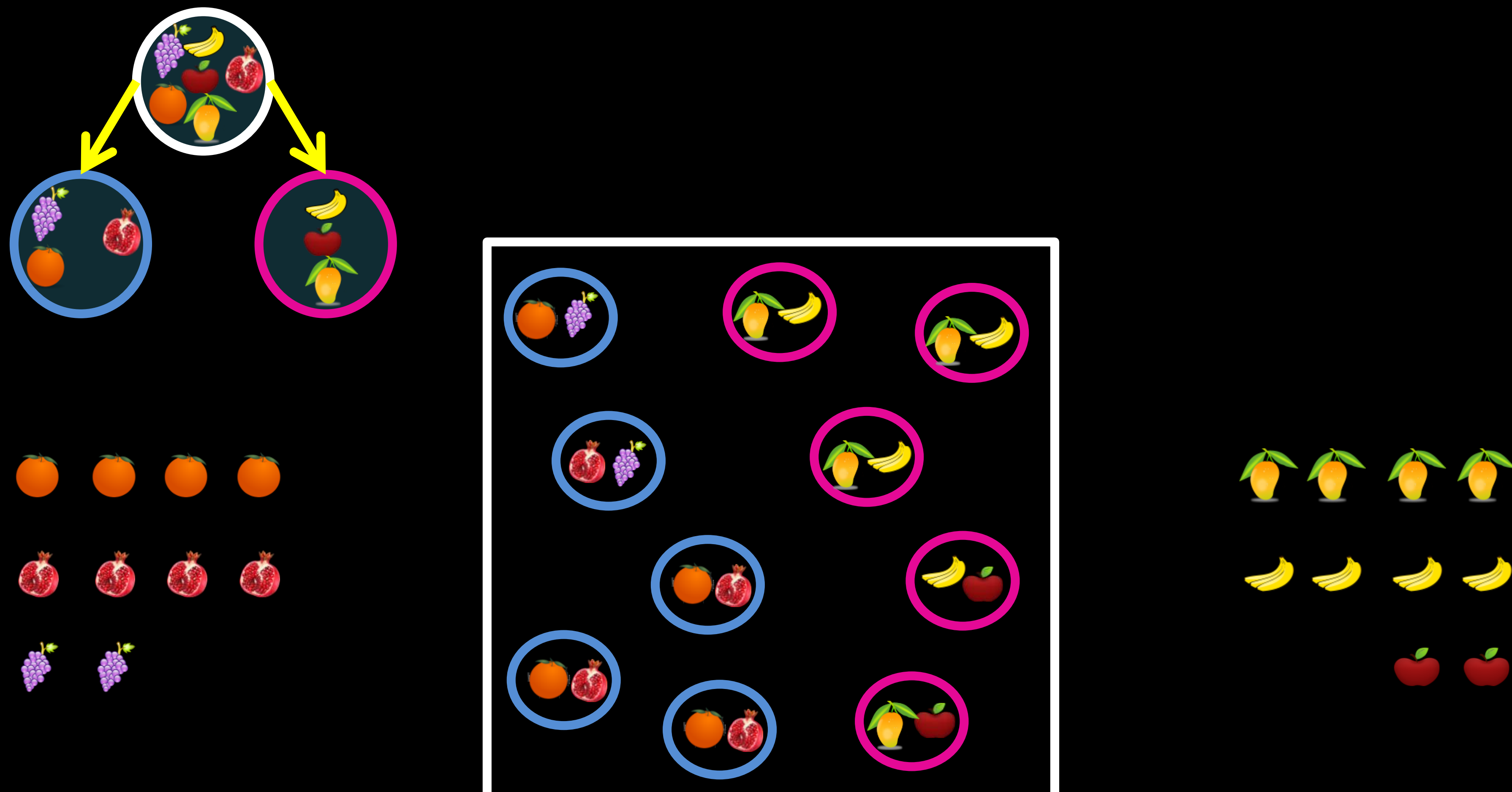






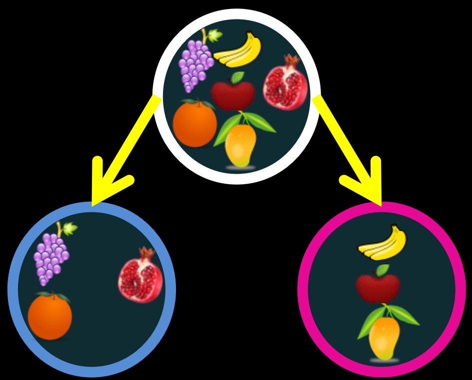
Optimizing nDCG

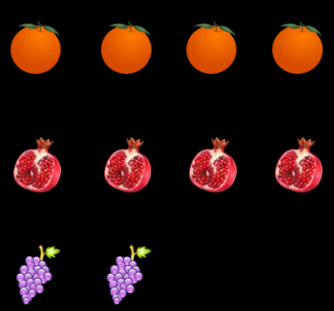
$$\mathrm{Min}_{\mathbf{w},\boldsymbol{\delta},\mathbf{r}^{\pm}} \; \|\mathbf{w}\|_1 + \sum_i C_\delta(\delta_i) \log\left(1 + e^{-\delta_i \mathbf{w}^t \mathbf{x}_i}\right) - C_r \sum_i \mathrm{nDCG}\left(\mathbf{r}^{\delta_i}\right)^t N_{\mathbf{y}_i} \mathbf{y}_i$$

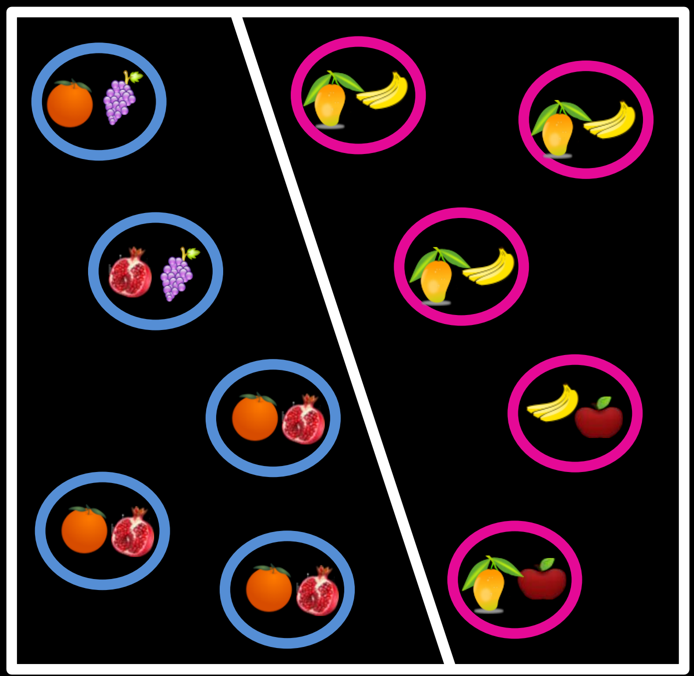


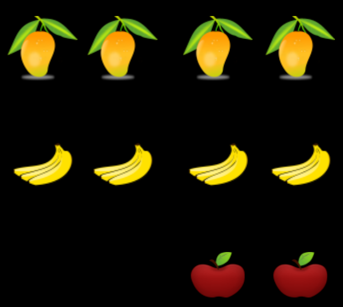
Optimizing nDCG – Hyperplane Separator

$$\mathrm{Min}_{\mathbf{w},\boldsymbol{\delta},\mathbf{r}^{\pm}} \quad \|\mathbf{w}\|_1 + \sum_i C_\delta(\delta_i) \log\left(1 + e^{-\delta_i \mathbf{w}^t \mathbf{x}_i}\right) - C_r \sum_i \mathrm{nDCG}\left(\mathbf{r}^{\delta_i}\right)^t N_{\mathbf{y}_i} \mathbf{y}_i$$









Data Set Statistics

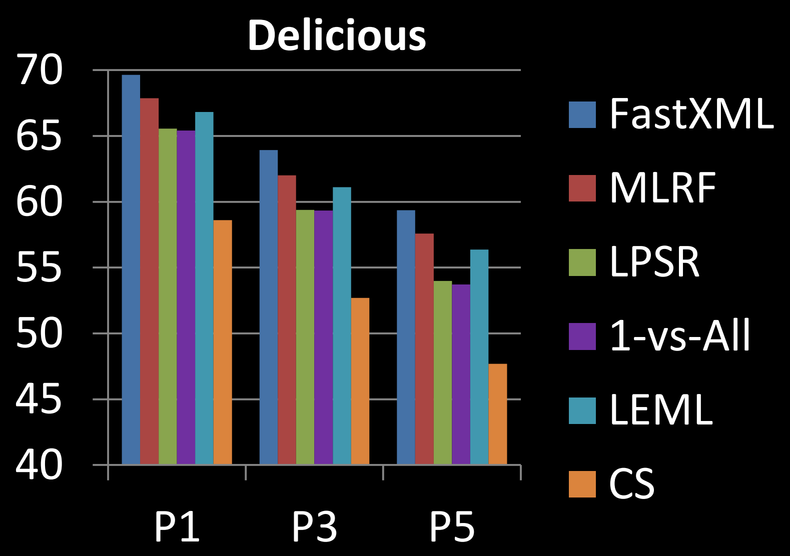
Small data sets

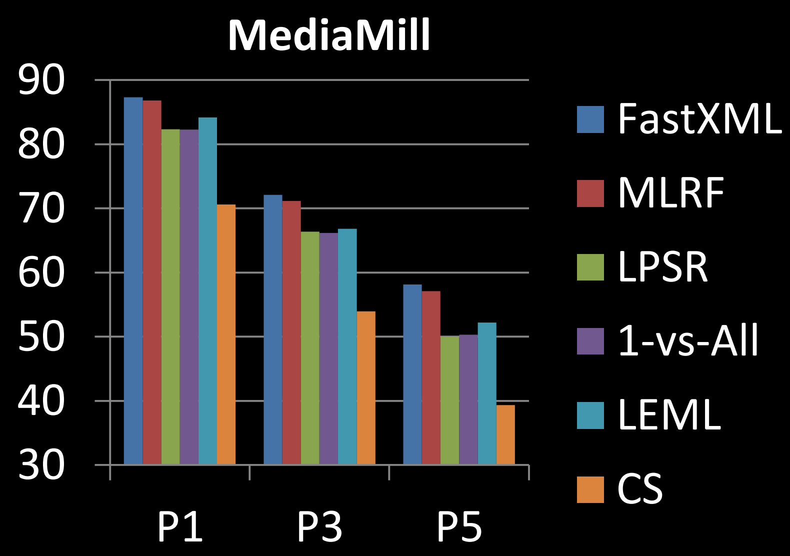
Data Set	# of Training Points	# of Test Points	# of Dimensions	# of Labels
Delicious	**12,920**	**3,185**	**500**	**983**
MediaMill	**30,993**	**12,914**	**120**	**101**
RCV1-X	**781,265**	**23,149**	**47,236**	**2,456**
BibTeX	**4,880**	**2,515**	**1,836**	**159**

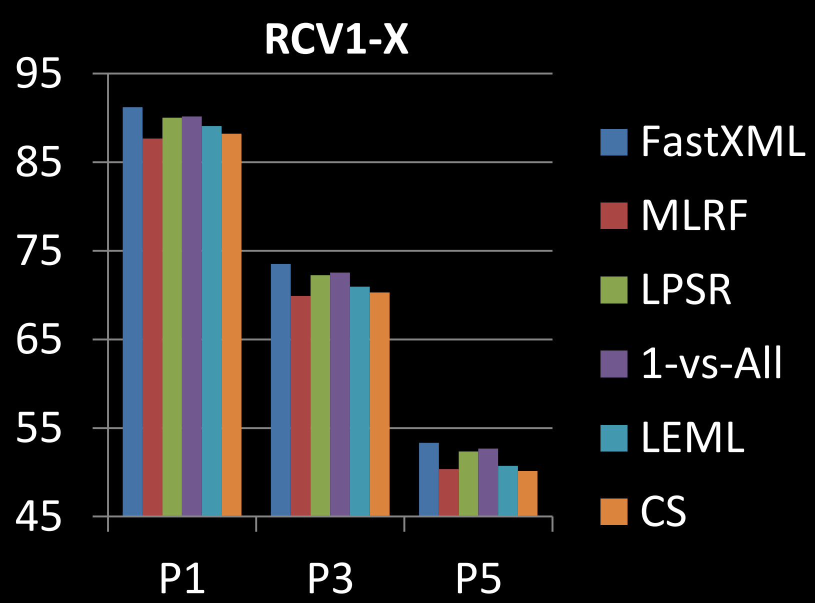
Large data sets

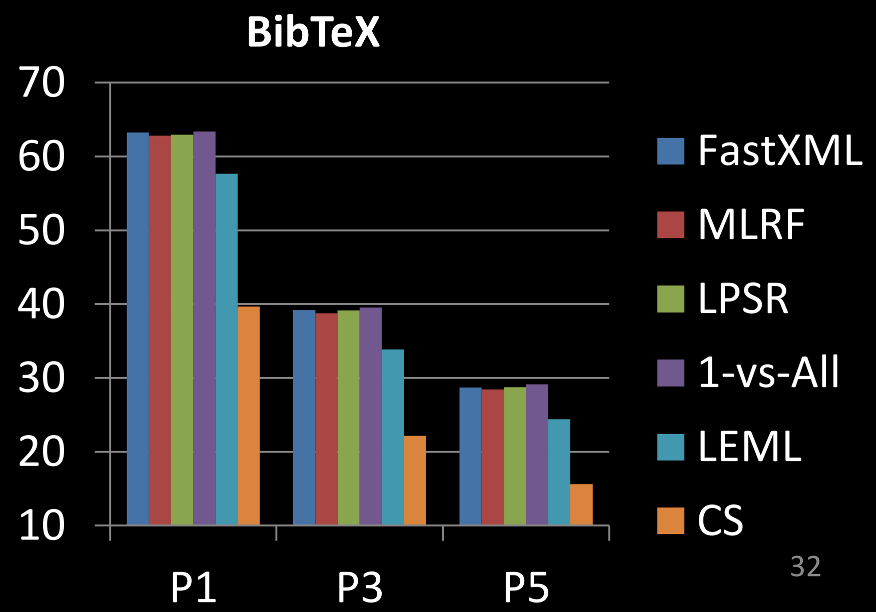
Data Set	# of Training Points (M)	# of Test Points (M)	# of Dimensions (M)	# of Labels (M)
WikiLSHTC	1.89	0.47	1.62	0.33
Ads-430K	1.12	0.50	0.088	0.43
Ads-1M	3.92	1.56	0.16	1.08
Ads-9M	70.46	22.63	2.08	8.84

Results on Small Data Sets



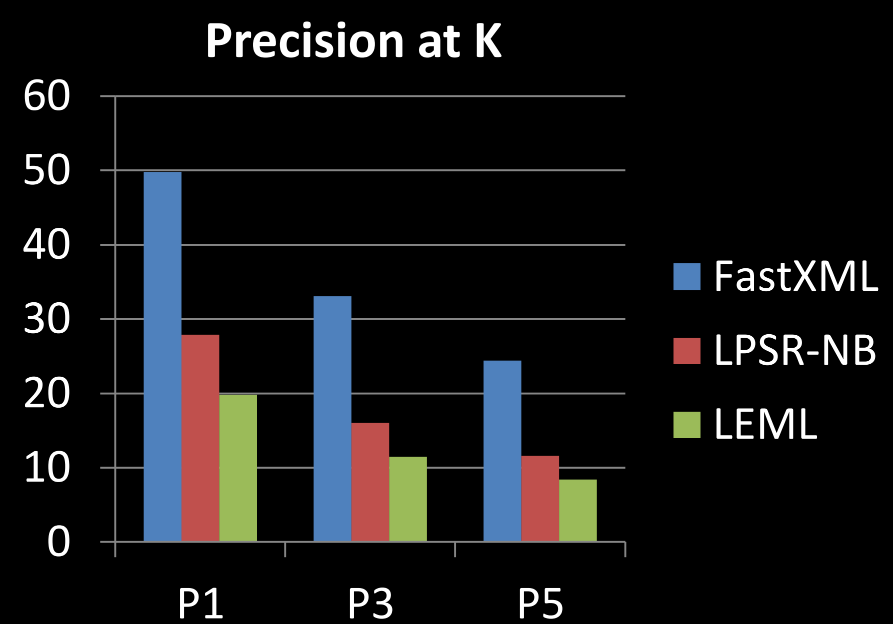


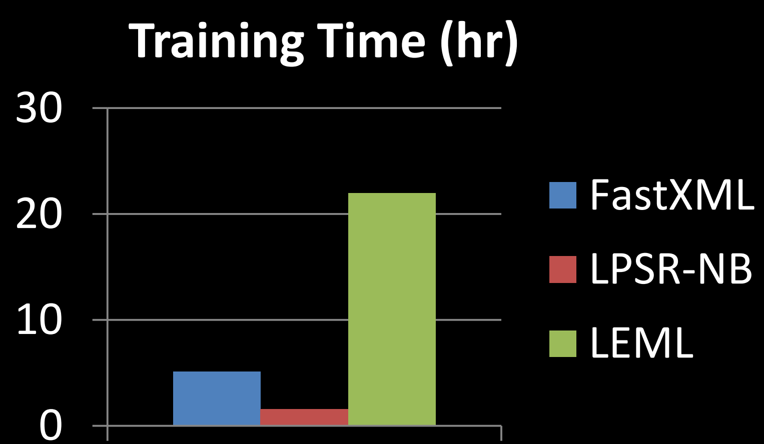


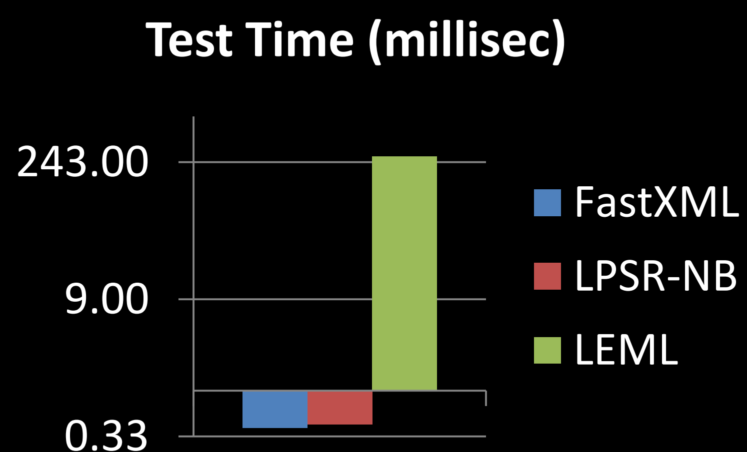


Large Data Sets - WikiLSHTC

Dataset Statistics	
Training Points	1,892,600
Features	1,617,899 (sparse)
Labels	325,056
Test Points	472,835



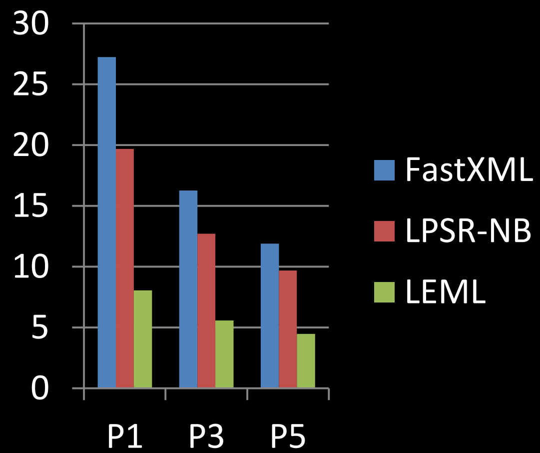




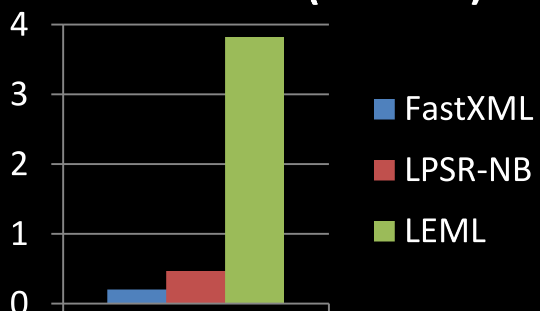
Large Data Sets - Ads

Ads-430K

Precision at K

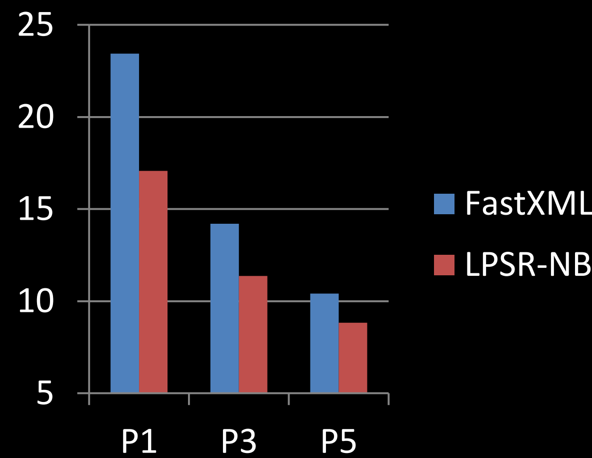


Test Time (millisec)

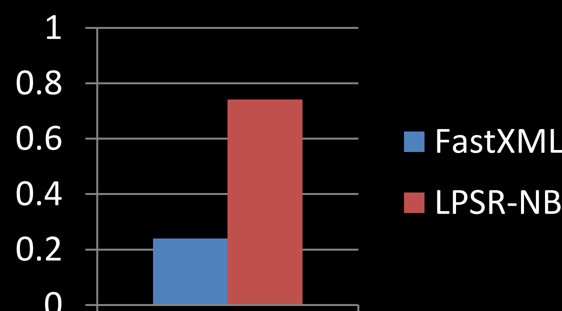


Ads-1M

Precision at K

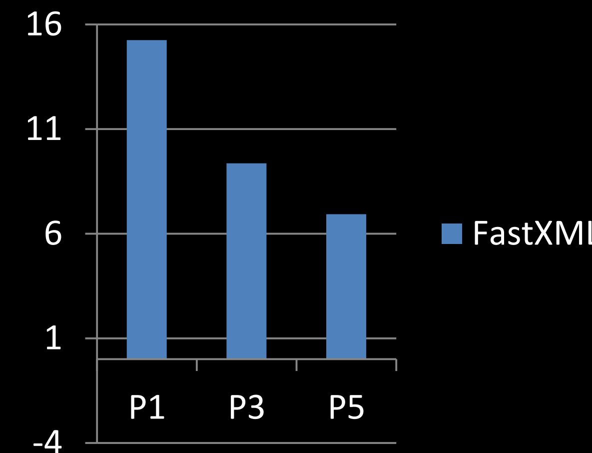


Test Time (millisec)

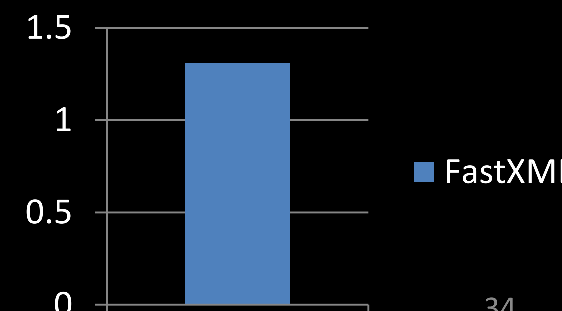


Ads-9M

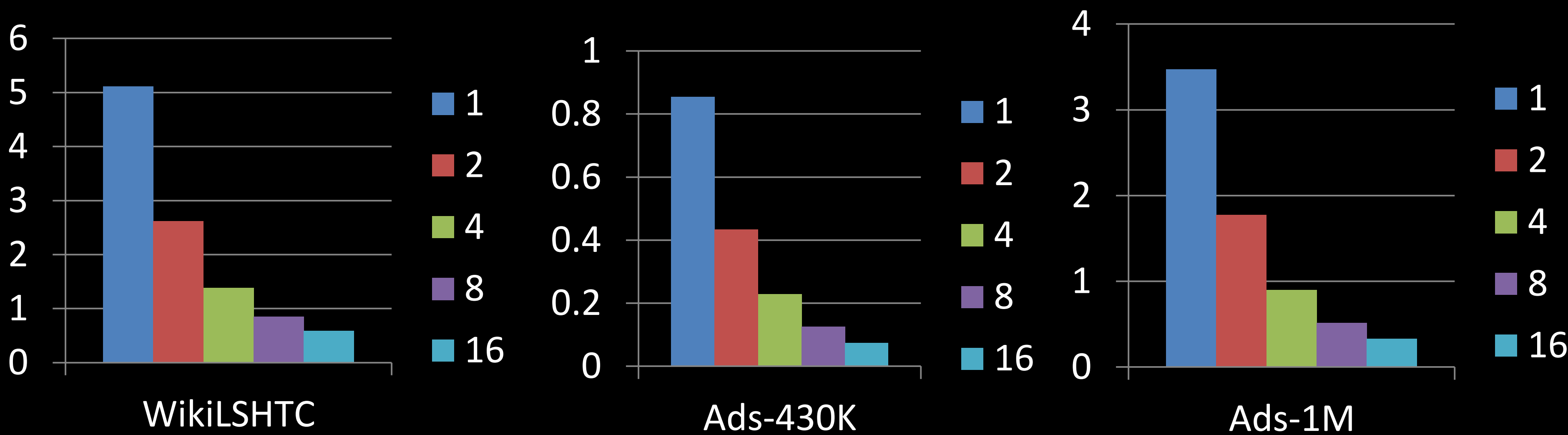
Precision at K



Test Time (millisec)



Training Times in Hours Versus Cores



Conclusions

- Extreme classification
  - Tackle applications with millions of labels
  - A new paradigm for recommendation
- FastXML
  - Significantly higher prediction accuracy
  - Can train on a single desktop
- Publications and code
  - WWW13, KDD14, NIPS15 paperps
  - Code and data available from my website

Unbiased Performance Evaluation

Himanshu Jain (IIT Delhi)
Yashoteja Prabhu (IIT Delhi)
Manik Varma (Microsoft Research)

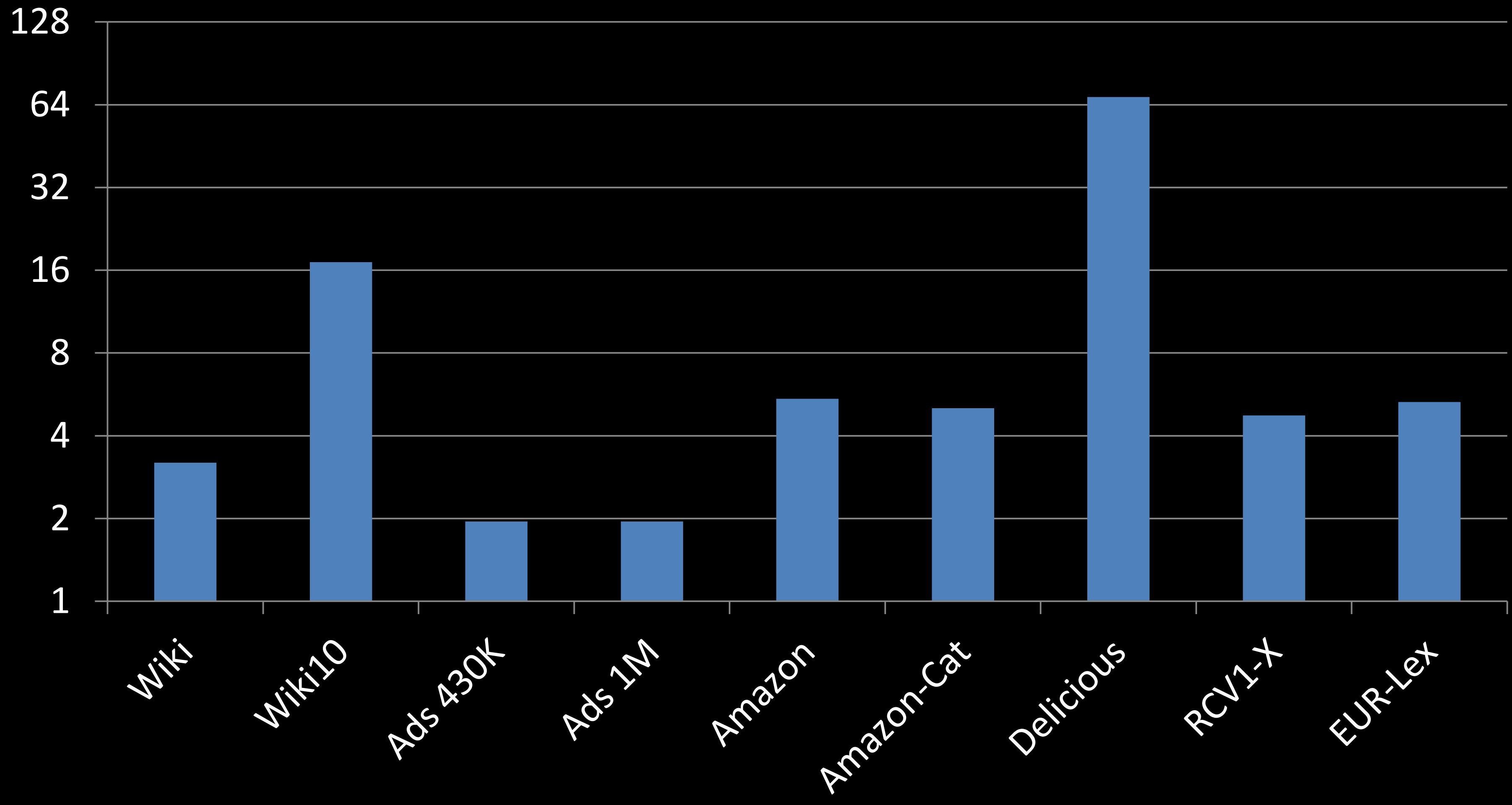
Traditional Loss/Gain Functions

- Hamming loss
- Subset 0/1 loss
- Precision
- Recall
- F-score
- Jaccard distance

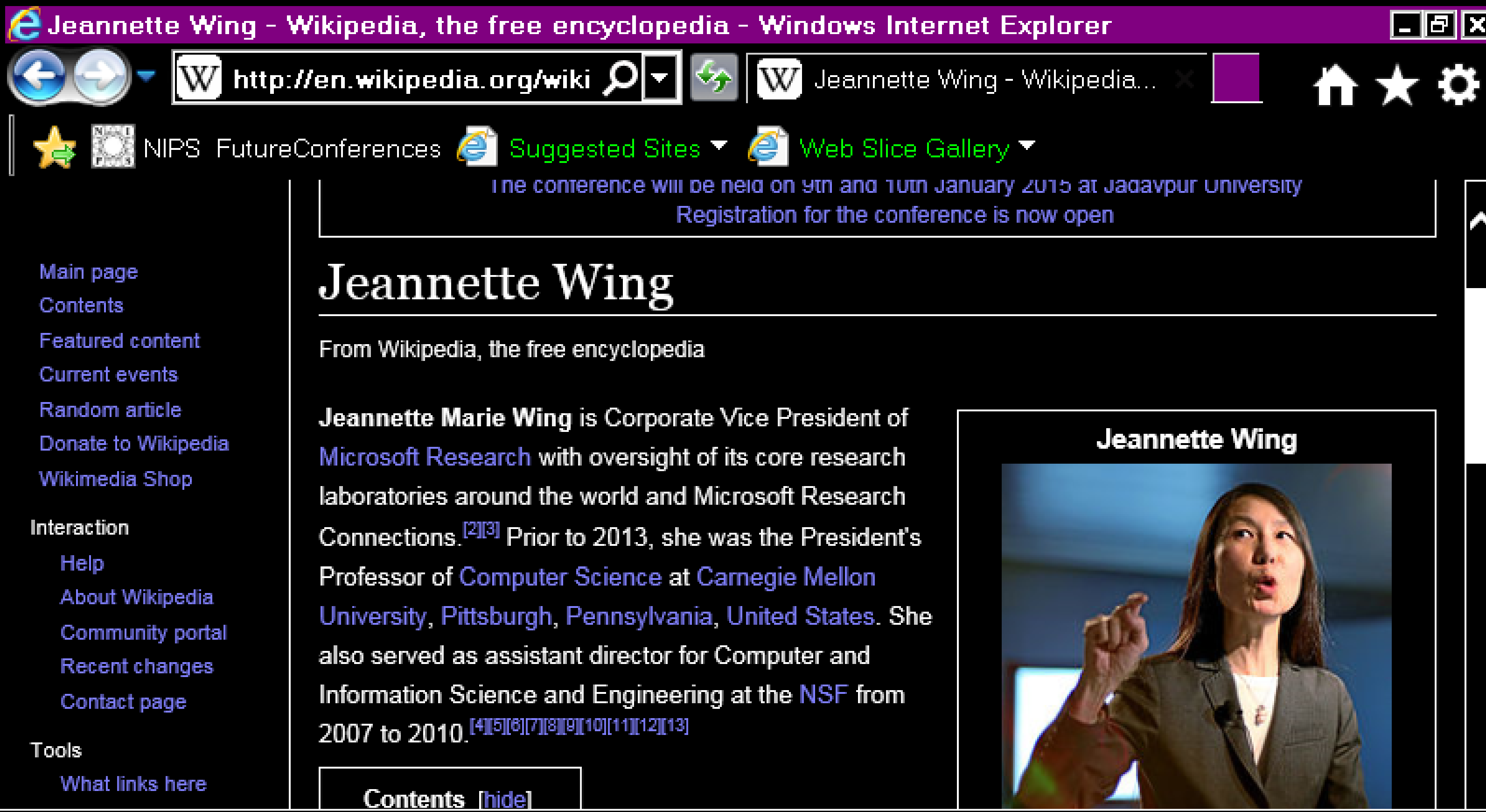
	Washington	Lincoln	Kennedy	Jefferson	Roosevelt
1	history	history	history	history	history
	politics	politics	politics	politics	politics
	people	people	people	people	people
	usa	usa	usa	usa	usa
	america	america	america	america	america
2	history	usa	leader	people	us citizen
	politics	america	writer	usa	19^{th} century born
	war	politician	american	thinker	us history
	-	-	-	philosopher	-
	-	-	-	-	-
3	usa	usa	president	president	usa
	first president	president	cuban missile crisis	founding fathers of the us	president
	founding fathers of the us	emancipation proclamation	project apollo	declaration of independence	attack on pearl harbour
	american revolutionary war	assassinated	assassinated	acquisition of louisiana	great depression
	whiskey rebellion	abolition of slavery	-	american revolutionary war	-

Average # of Positive Labels per Point



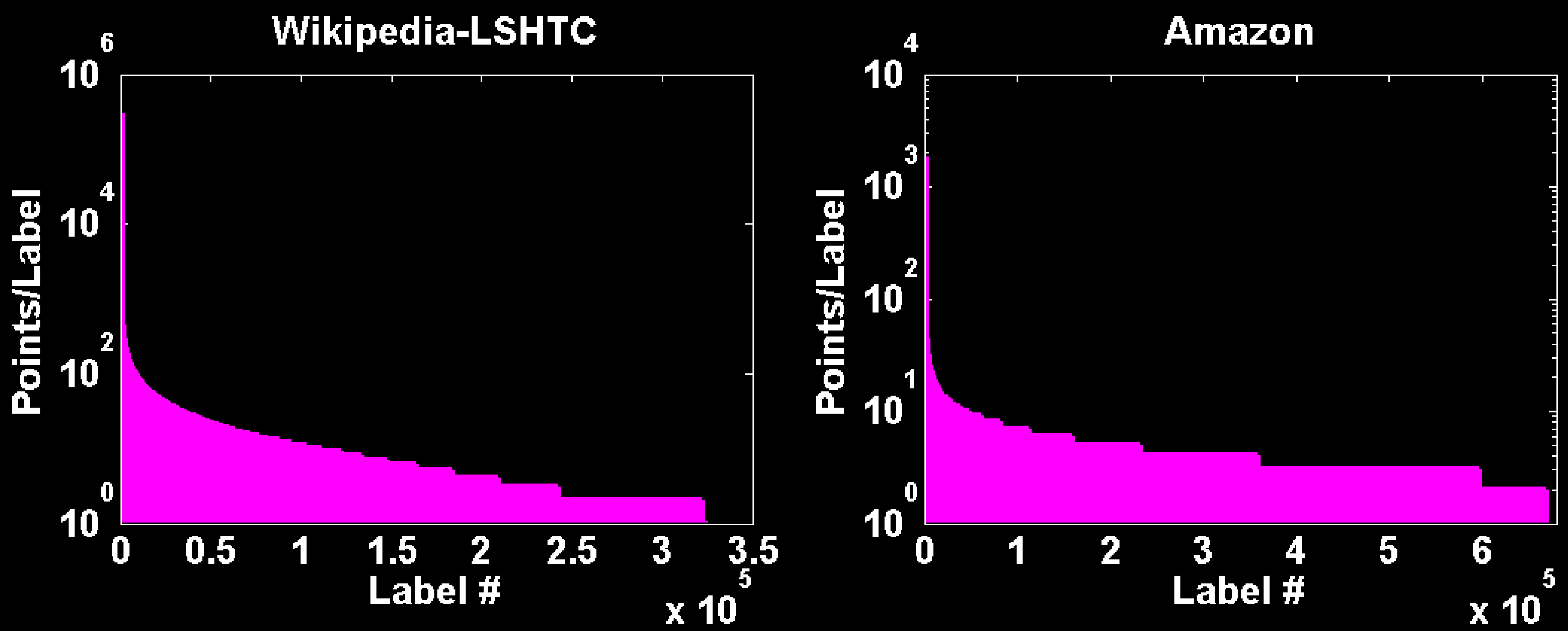
- +ve labels are more important than –ve ones

Missing Labels



Labels: Living people, American computer scientists, Formal methods people, Carnegie Mellon University faculty, Massachusetts Institute of Technology alumni, Academic journal editors, Women in technology, Women computer scientists.

Tail Labels



- # of relevant labels > # of prediction slots
- Not all positive labels are equally important

Extreme Loss/Gain Functions

- Accuracy – handle biased ground truth
- Rareness / Novelty
- Diversity
- Explainability

Open Research Questions

- Applications
- Obtaining good quality training data
- Log time and space training and prediction
- Obtaining discriminative features at scale
- Extreme loss functions
- Performance evaluation
- Dealing with tail labels and label correlations
- Dealing with missing and noisy labels
- Explore/exploit for tail labels
- Statistical guarantees
- Fine-grained classification

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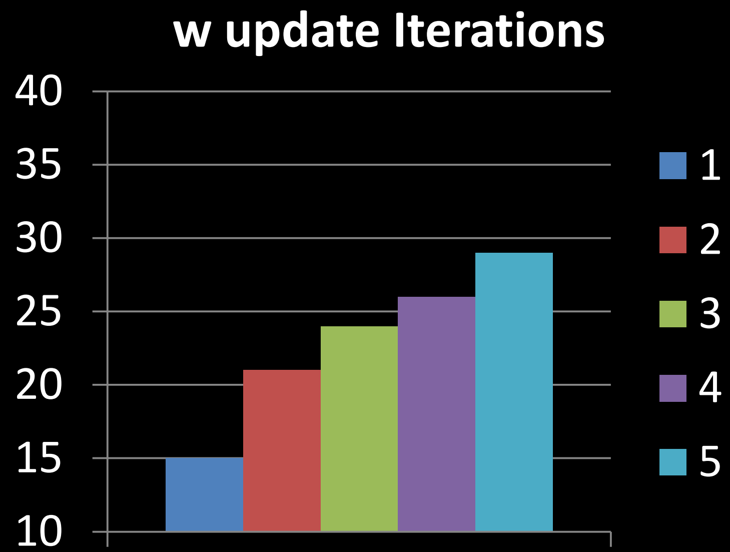
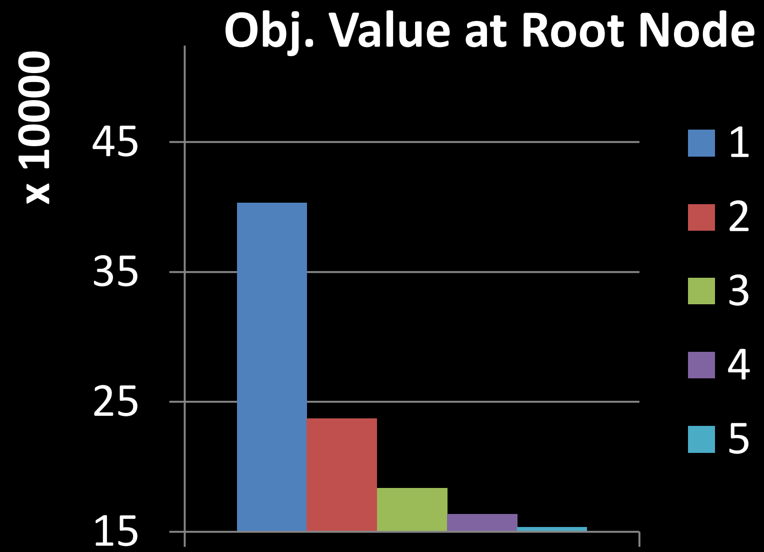
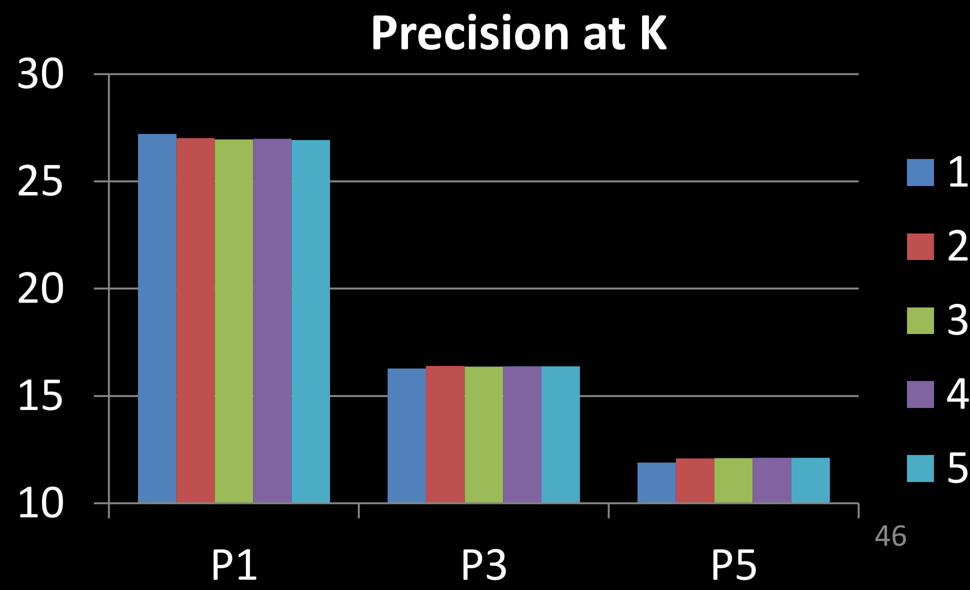
Purushottam Kar
Abhirup Nath
Ambuj Tewari
C. Yeshwanth

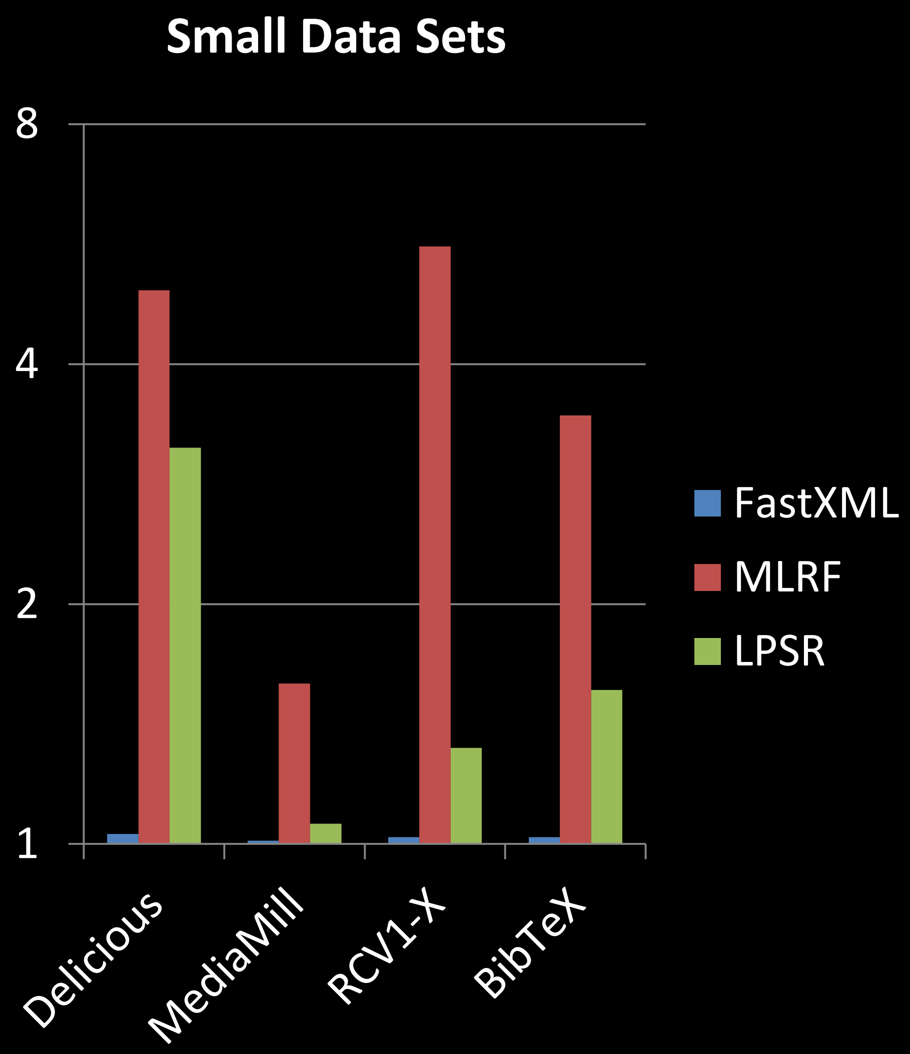
Multiple Iterations - Ads-430K

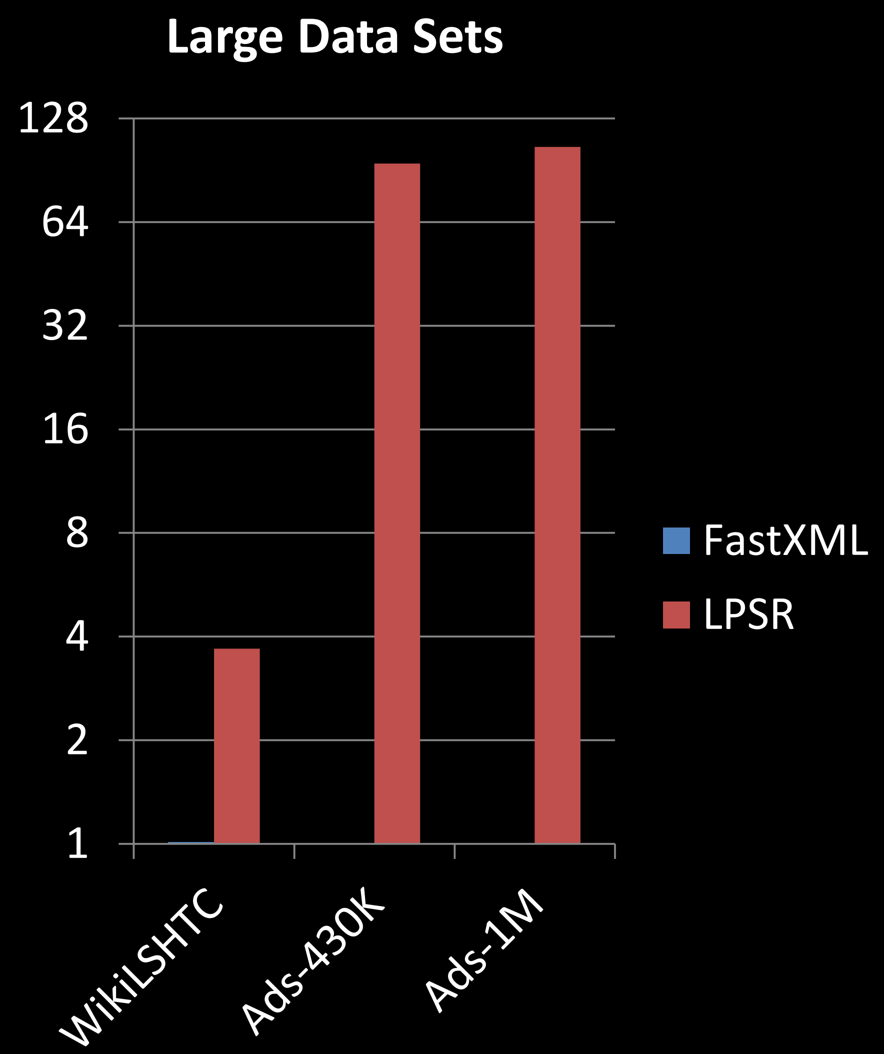




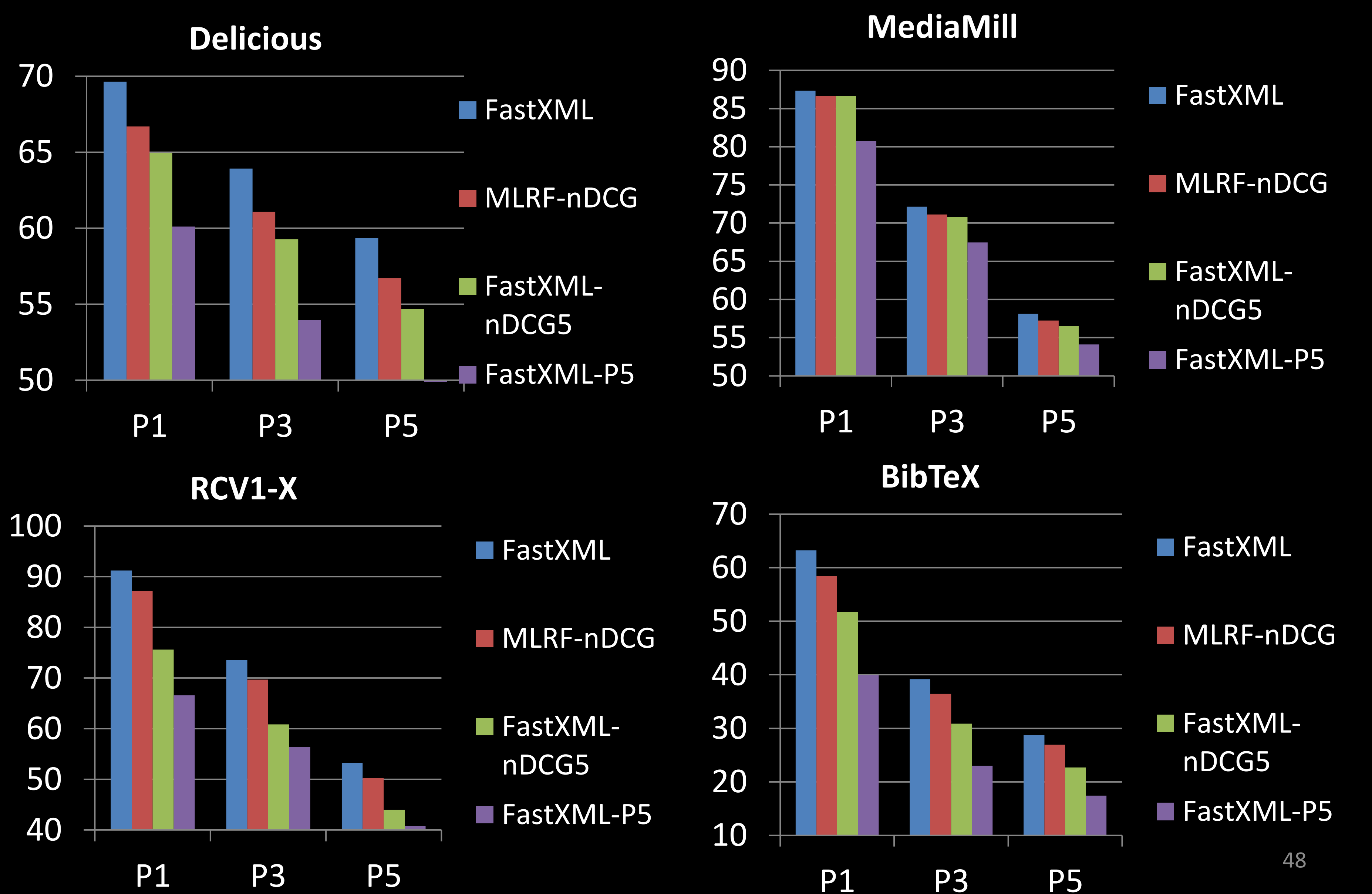


Tree Imbalance

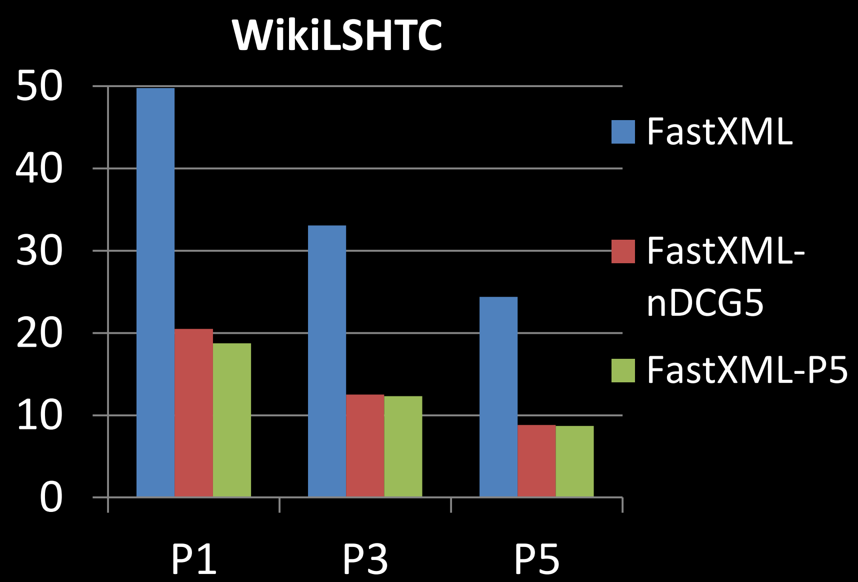


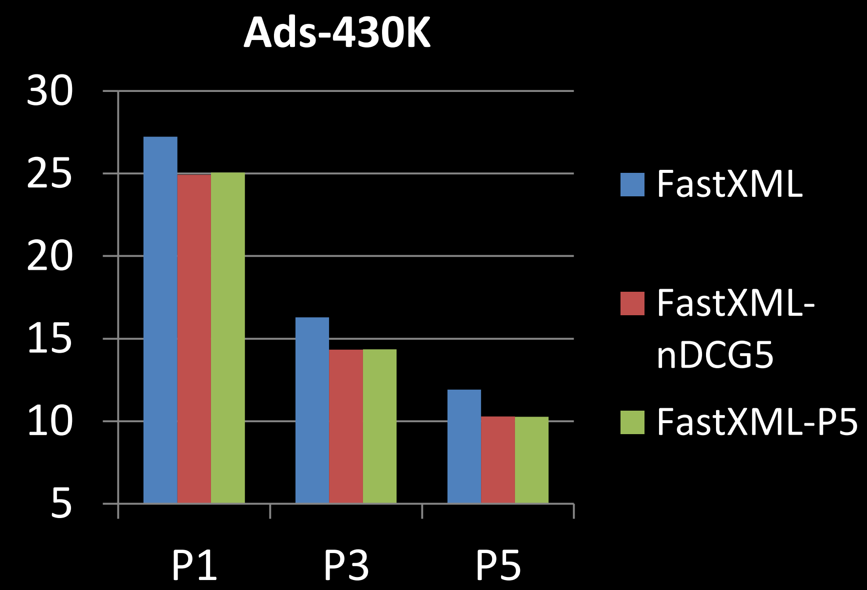


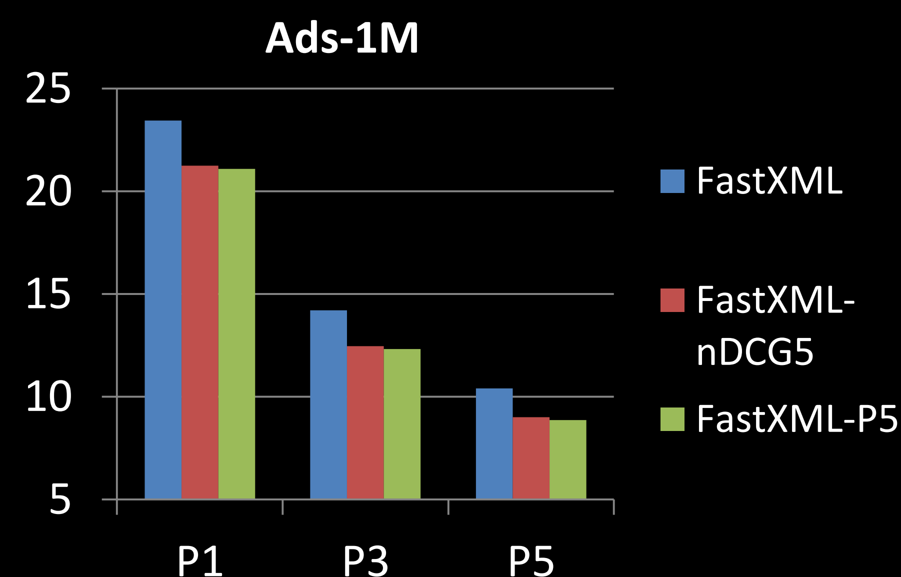
Variants of FastXML - Small Data Sets



Variants of FastXML - Large Data Sets







Random Tree Selection