

# The Maximum Entropy Method for Analyzing Retrieval Measures

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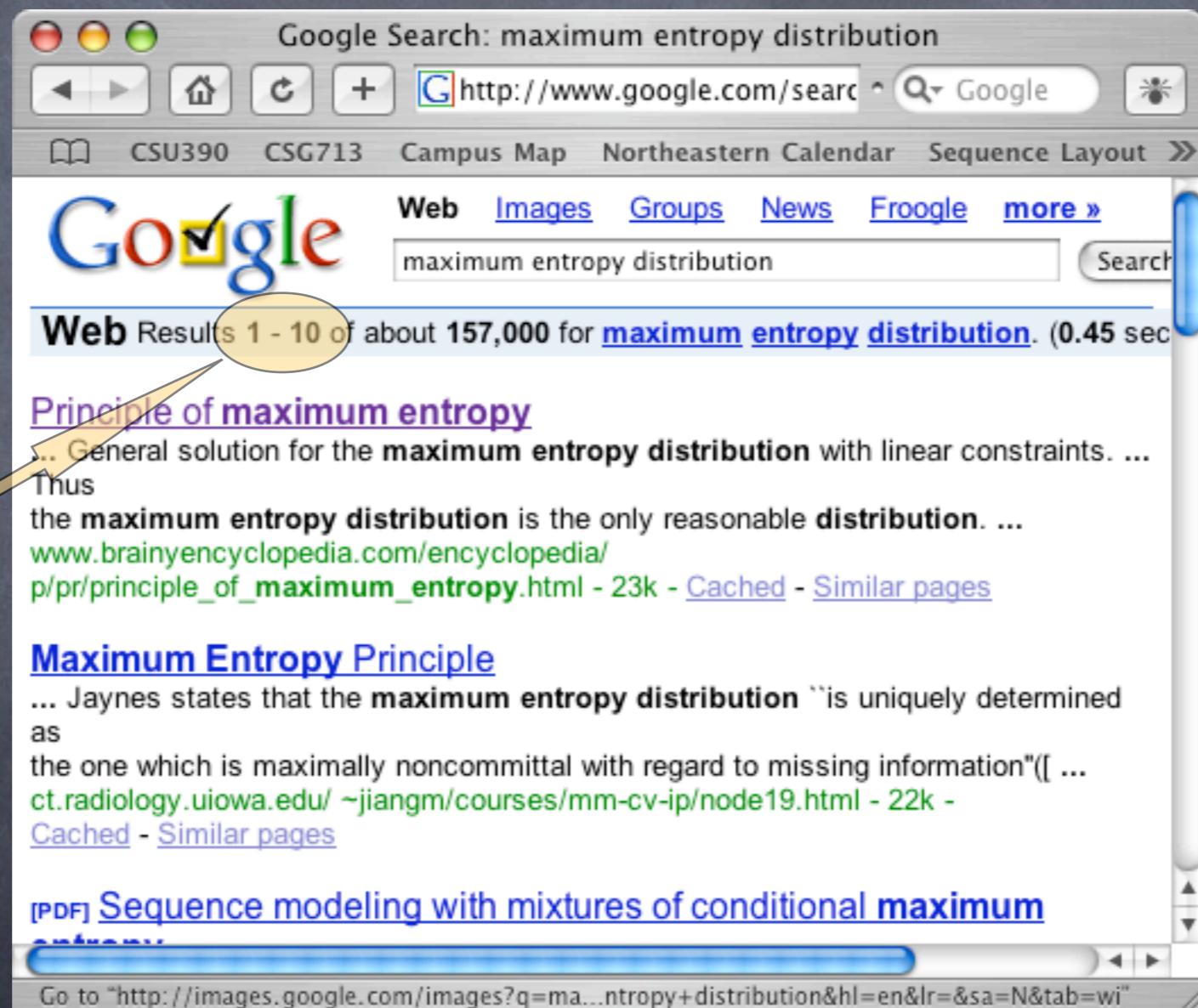
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# Evaluation Measures: Top Document Relevance



# Evaluation Measures: First Page Relevance



# Natural Question...

- Many measures of retrieval performance
  - 23 standard measures used in TREC
- Are some measures “better” than others?
  - system-oriented vs. user-oriented measures
- Q: What can be learned from a measure?
- A: Good overall measures:
  - reduce uncertainty about underlying phenomenon
  - allow one to infer underlying phenomenon
- E.g., Health:
  - BMI vs. blood pressure vs. cholesterol vs. shoe size

# Research Goals

- What can be reasonably inferred from a measure?
  - maximum entropy method...
- How good are those inferences?
  - compare inferences to reality (e.g., TREC)
- Assess quality of measures
  - error, prediction, reduction in uncertainty

# Outline

- Introduction
- Standard measures for query retrieval
- The maximum entropy method
  - dice example
  - measures as constraints
- MEM for query retrieval measures
- Experimental results

# Evaluation Measures Setup

- Ranked list of retrieved documents
- Binary relevance judgments
- Good performance:
  - “many” relevant docs “high” in list

# Traditional IR Measures

- Precision of top k documents, for k:
  - 5, 10, 15, 20, 30, 100, 200, 500, 1000
- R-precision:
  - precision of top R documents,  
 $R = \# \text{ relevant docs}$  where
- Average precision:
  - average of precisions at all R relevant documents...

# Traditional IR Measures: Average Precision

List:	R	1/1
	N	
	R	2/3
	N	
	N	
	R	3/6
	N	
	N	
	N	
	R	4/10

$$AP = \frac{1 + 2/3 + 3/6 + 4/10}{4} \approx 0.6417$$

# Most Commonly Used IR Measures

- Average precision
- Precision at 10 (30, etc.) documents
- R-precision
- Precision-recall curves...

# Visualizing Retrieval Performance: Precision-Recall Curves

List:

R N R N R N R N R N R



# Analyzing Retrieval Measures: Setup

- A list or its P-R curve defines performance
- How much does a measure reduce one's uncertainty in the underlying list or its P-R curve?
- Good measures: large reduction in uncertainty
- Poor measures: little or no reduction in uncertainty
- How to measure reduction in uncertainty?
  - Maximum entropy method...

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# Maximum Entropy Method: Dice Example

- Given an unknown six-sided dice, what is probability for each die face (1, 2, 3, 4, 5, 6)?
- Under-constrained problem
  - most “reasonable” answer is uniform ( $1/6, 1/6, \dots, 1/6$ )
- What if average die roll is 4.5?
  - problem still under-constrained, but what is the most “reasonable” answer?
  - maximum entropy method to the rescue...

# Maximum Entropy Method

- Goal: infer probability distribution (belief) from statistics (measures or constraints) over that distribution
- Uses: prediction, coding, gambling, etc.
- MEM dictates the most “reasonable” solution

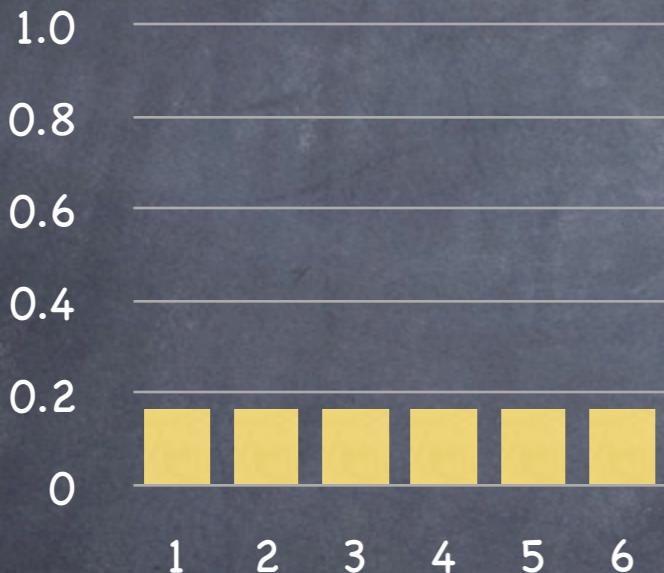
# Back to Dice Example

- Average die roll is 4.5; what is distribution?
- One solution:
  - Principle of “maximal ignorance:” pick distribution which is least predictable (most random) subject to constraints
  - How to measure randomness? Entropy  $H(\vec{p}) = \sum_{i=1}^6 p_i \lg(1/p_i)$
  - Thus, max entropy distribution subject to constraints

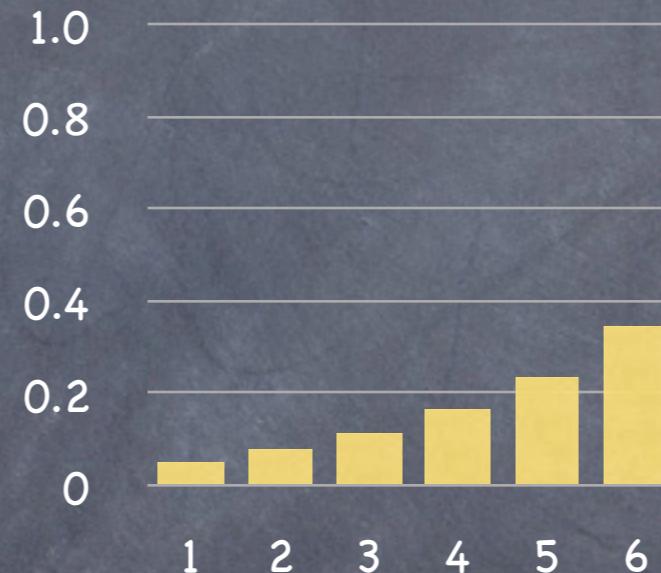
# Mathematical Justification

- Entropy Concentration Theorems
  - “weak” and “strong”
- Nature favors maximum entropy solutions
  - e.g., temperature and particle speed

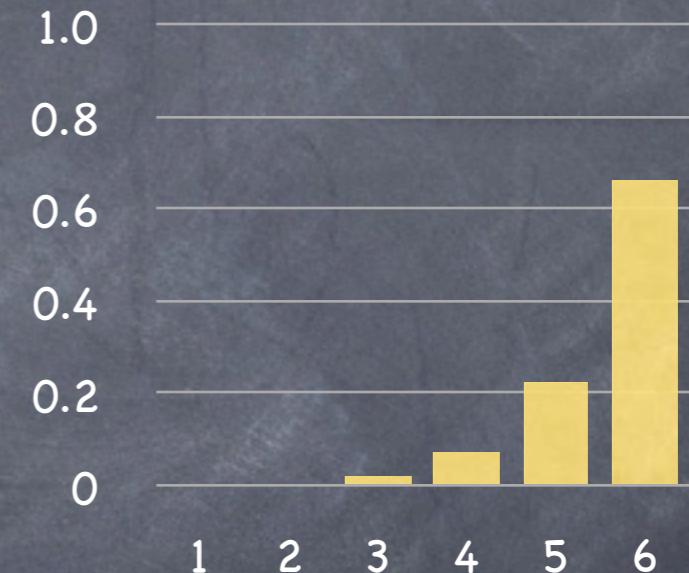
# Max Entropy Distributions: Dice Examples



$$E[X] = 3.5$$



$$E[X] = 4.5$$



$$E[X] = 5.5$$

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  - properties of the maximum entropy distribution
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# MEM for IR Measures: An Analogy

Problem	Events	Distribution	Constraint
Dice	die faces	over die faces	expected die roll
IR	lists	over lists	expected AP, RP, P@10

# IR Setup: Distribution over Lists

- possible relevance list  $(x_1, x_2, \dots, x_m)$
- distribution over lists  $p(x_1, x_2, \dots, x_m)$
- independence assumption
  - $p(x_1, x_2, \dots, x_m) = p_1(x_1) \cdot p_2(x_2) \cdots p_m(x_m)$
- probability-at-rank  $p_i = p_i(x_i)$

# How to Find Max Ent Dist?

- Assumption:  $p(x_1, x_2, \dots, x_m) = p_1(x_1) \cdot p_2(x_2) \cdots p_m(x_m)$
- Entropy:  $H(p(x_1, \dots, x_m)) = \sum_{i=1}^m H(p_i)$
- Constraints:
  - measure (AP, RP, P@10)
  - total number of relevant documents R

# Setup for PC@10 Constraint

- Maximize:  $\sum_{i=1}^m H(p_i)$
- Subject to:

$$\sum_{i=1}^{10} p_i = 10 \cdot \text{PC}(10)$$

- $\sum_{i=1}^m p_i = R$

# Setup for RP Constraint

- Maximize:  $\sum_{i=1}^m H(p_i)$
- Subject to:

$$\sum_{i=1}^R p_i = R \cdot \text{RP}$$

- $\sum_{i=1}^m p_i = R$

# Setup for AP Constraint

- Maximize:  $\sum_{i=1}^m H(p_i)$

- Subject to:

$$\sum_{i=1}^m \left( \frac{p_i}{i} \left( 1 + \sum_{j=1}^{i-1} p_j \right) \right) = R \cdot AP$$

- $\sum_{i=1}^m p_i = R$

# Solutions

- Analytical: Lagrange multipliers
- Numerical: MatLab, Mathematica, etc.

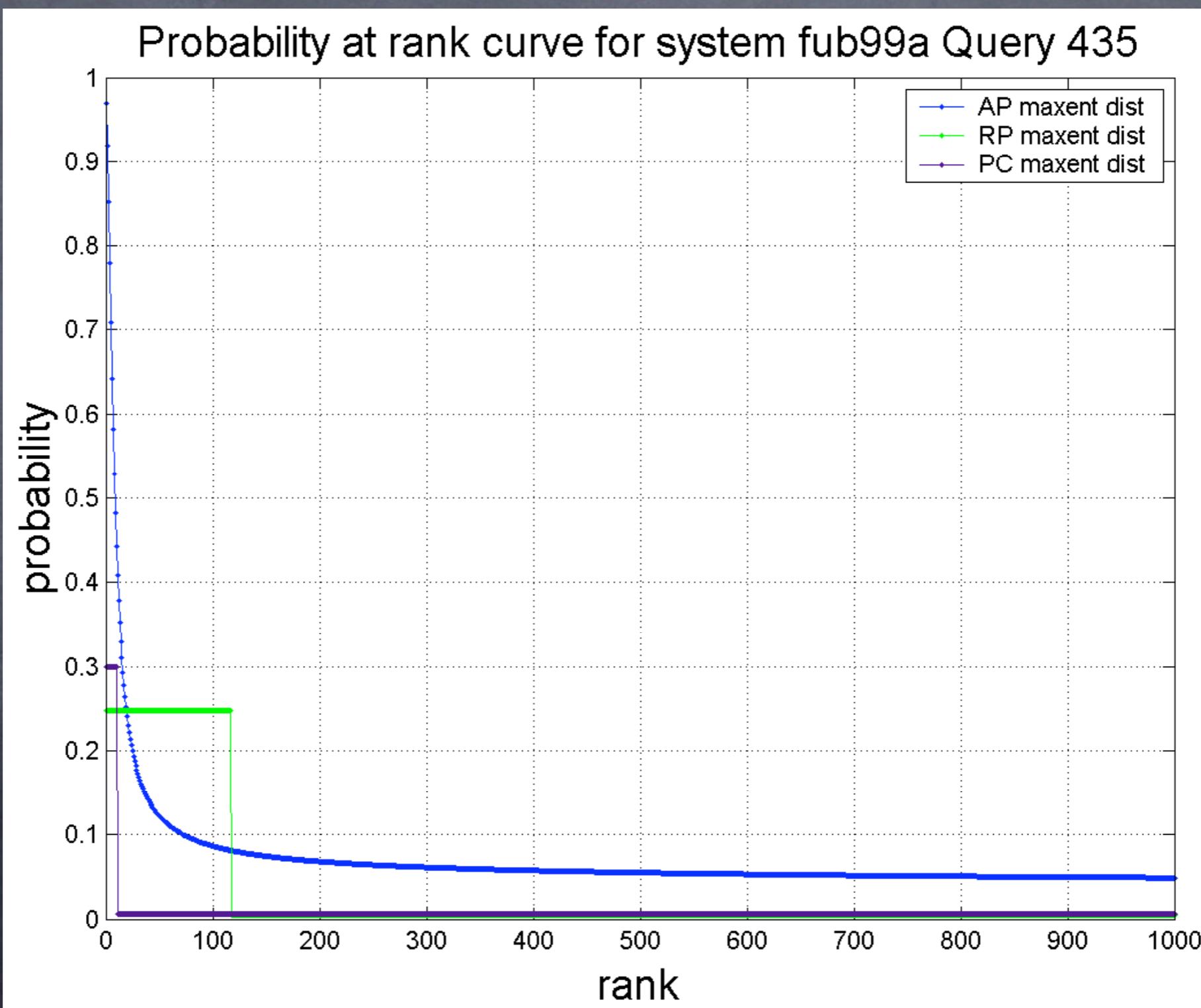
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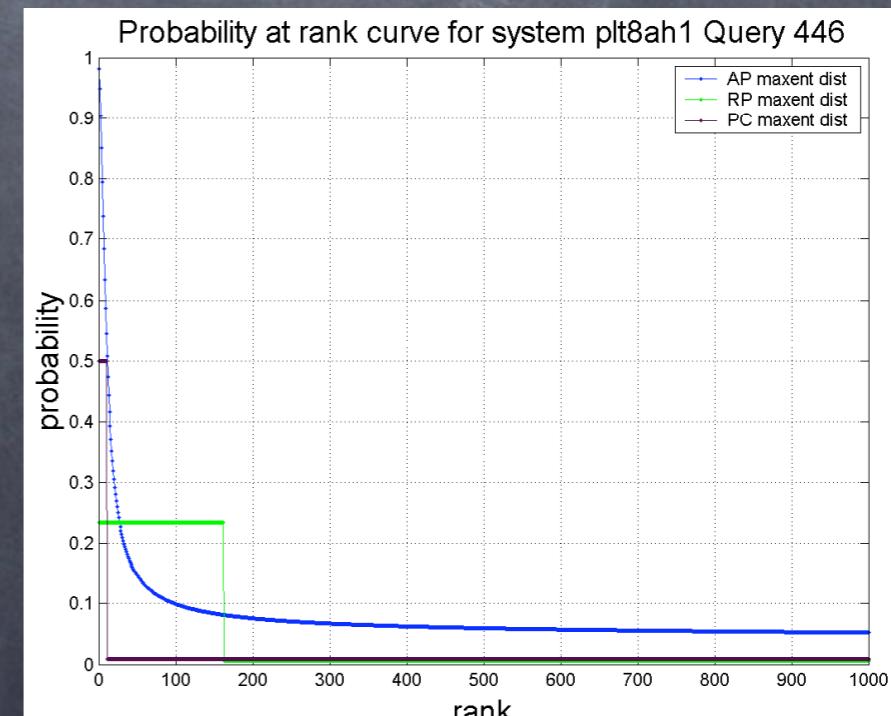
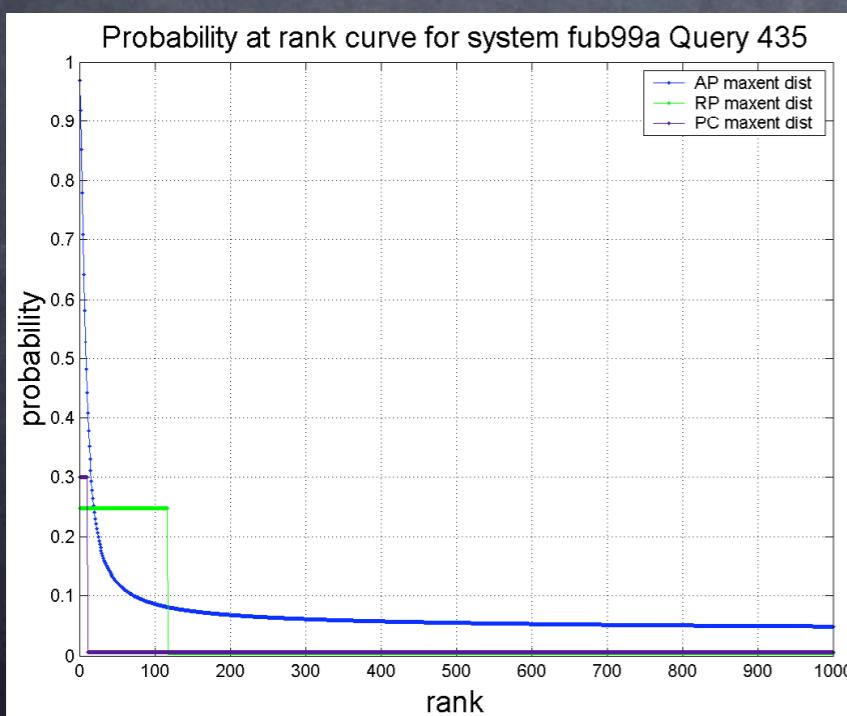
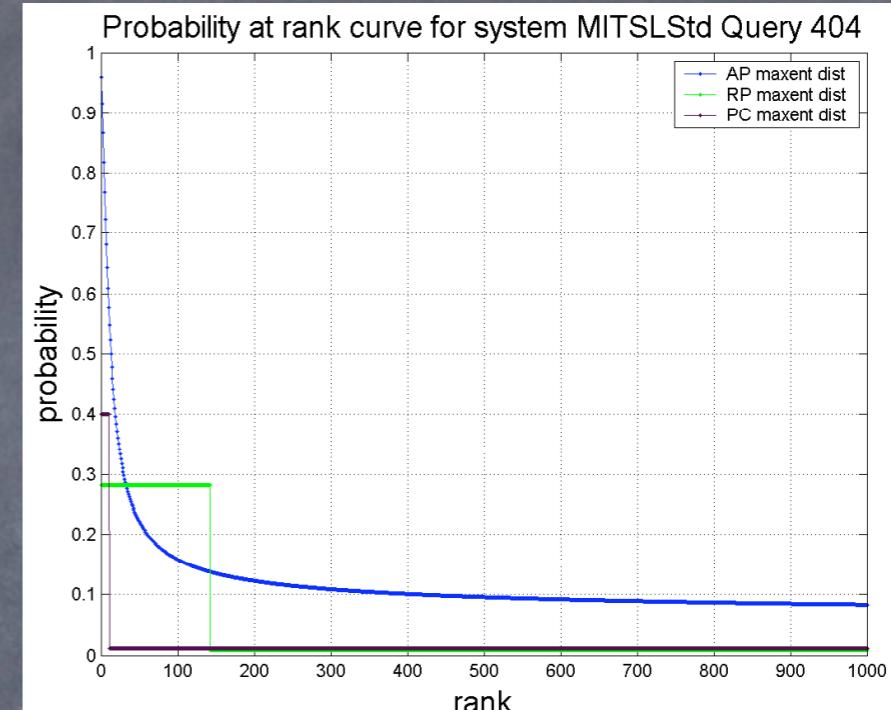
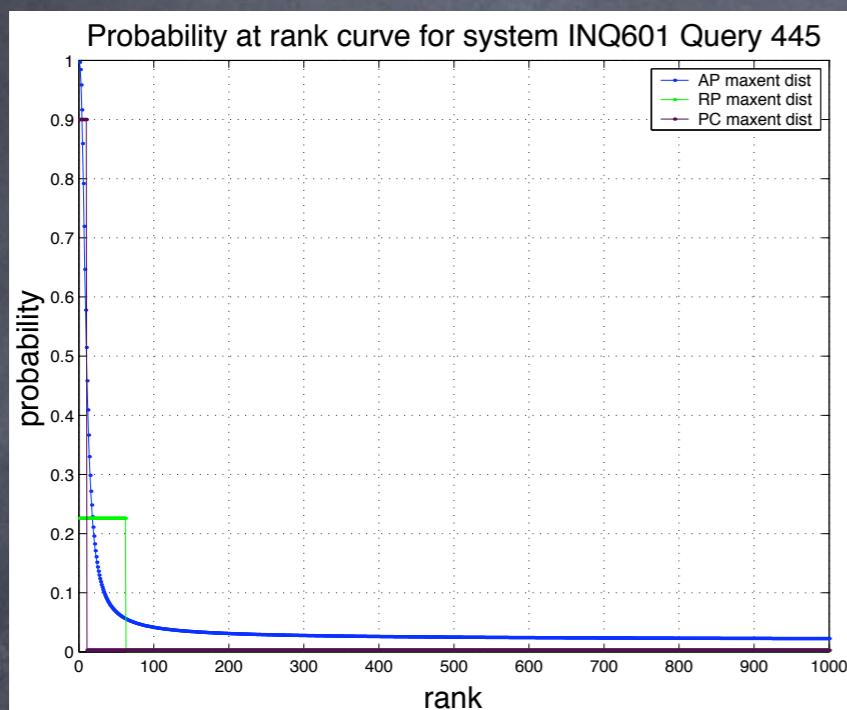
# Experimental Results

- Take actual lists from TREC conference
- Compute AP, RP, P@10
- Find max ent dist for these constraints
- Compare to actual list

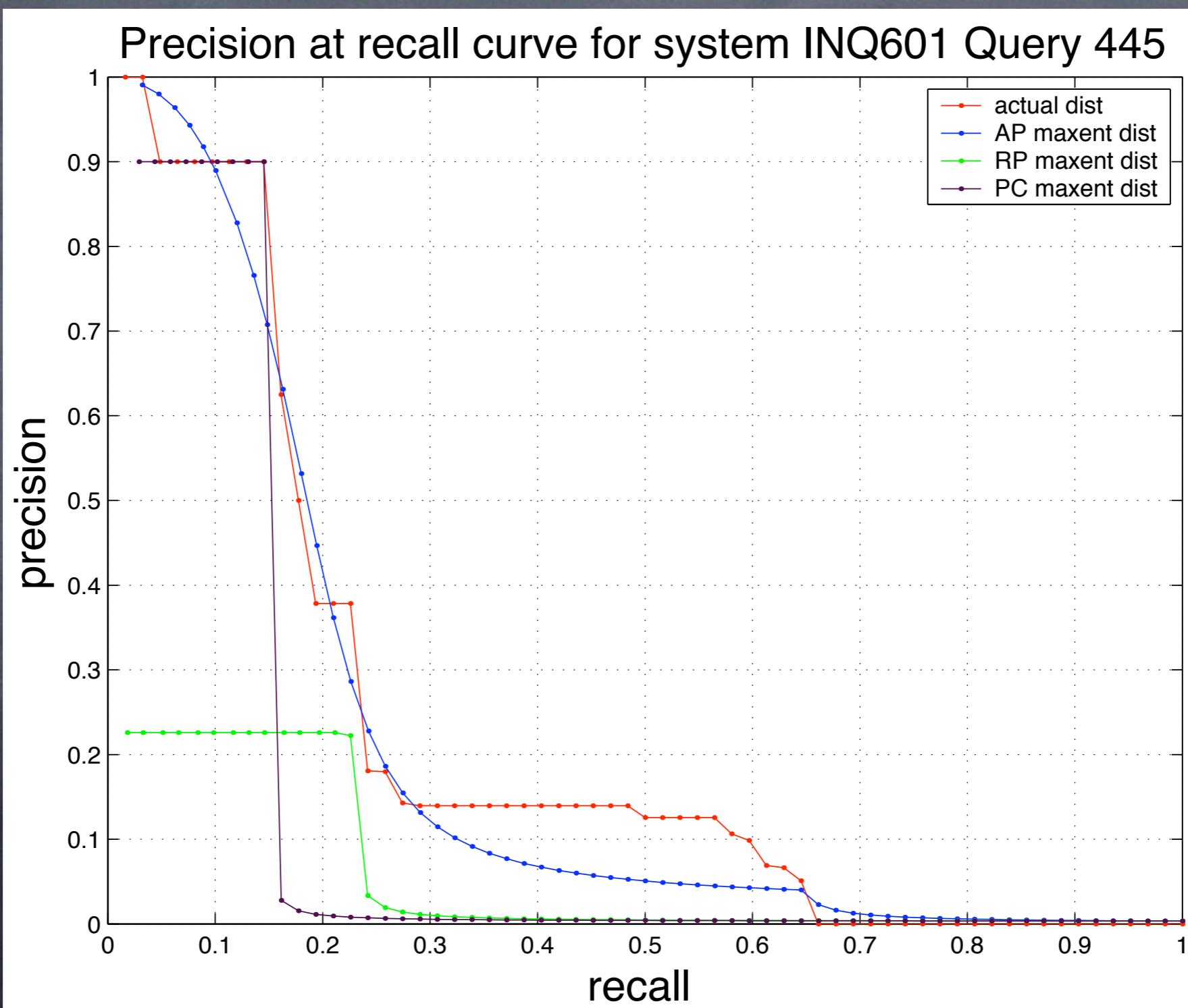
# Inferred Probability at Rank



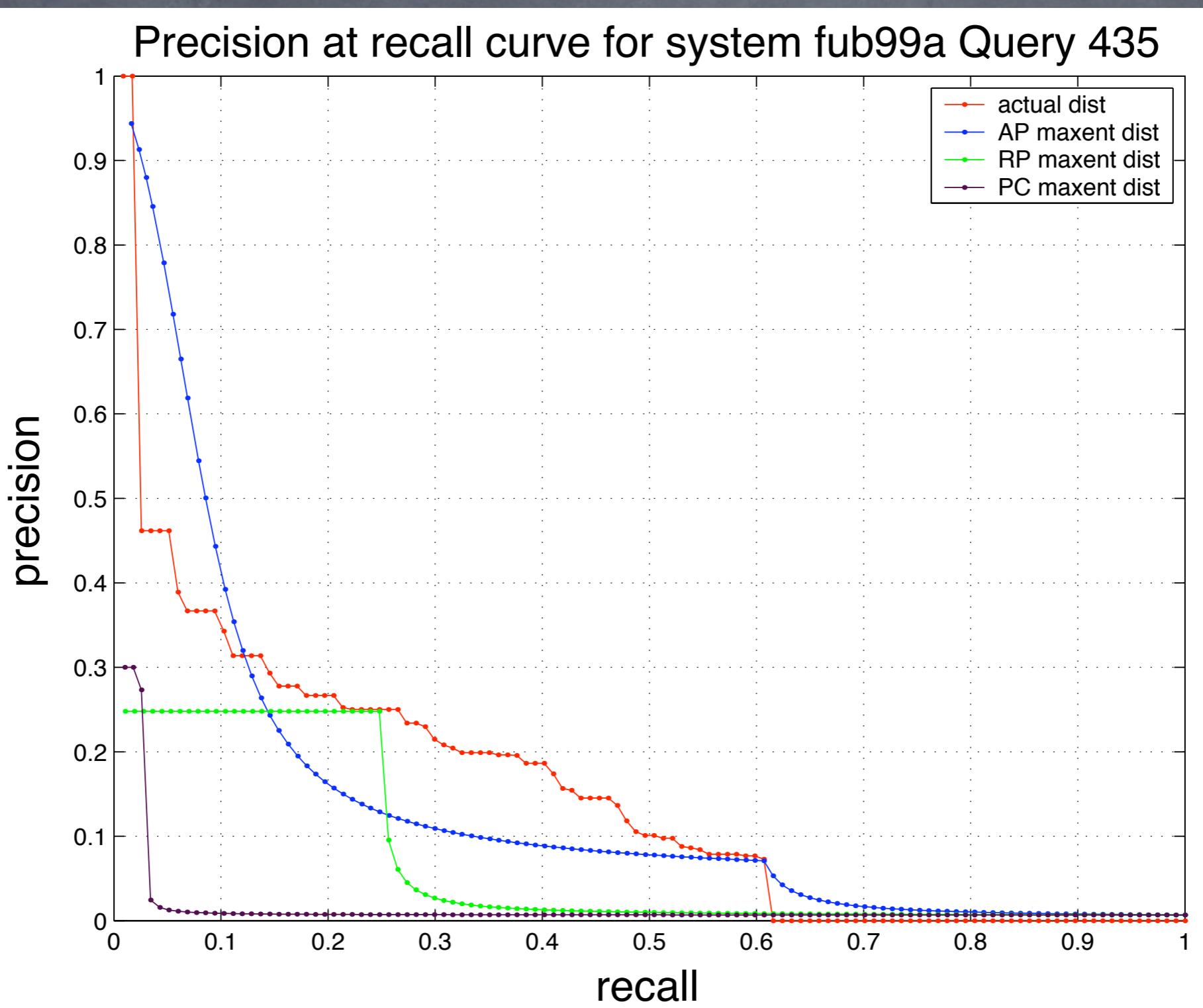
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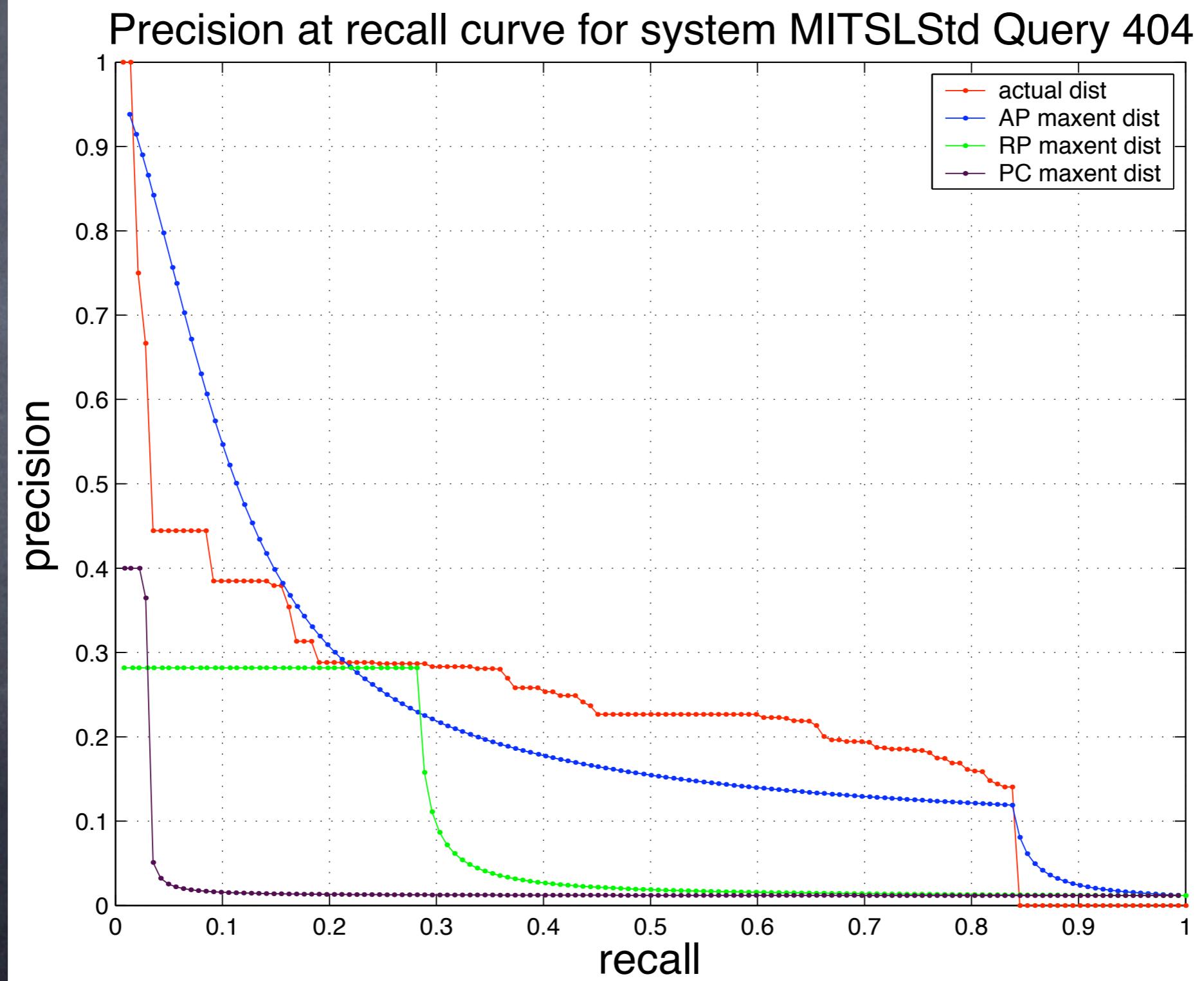
# Actual and Inferred P-R Curves



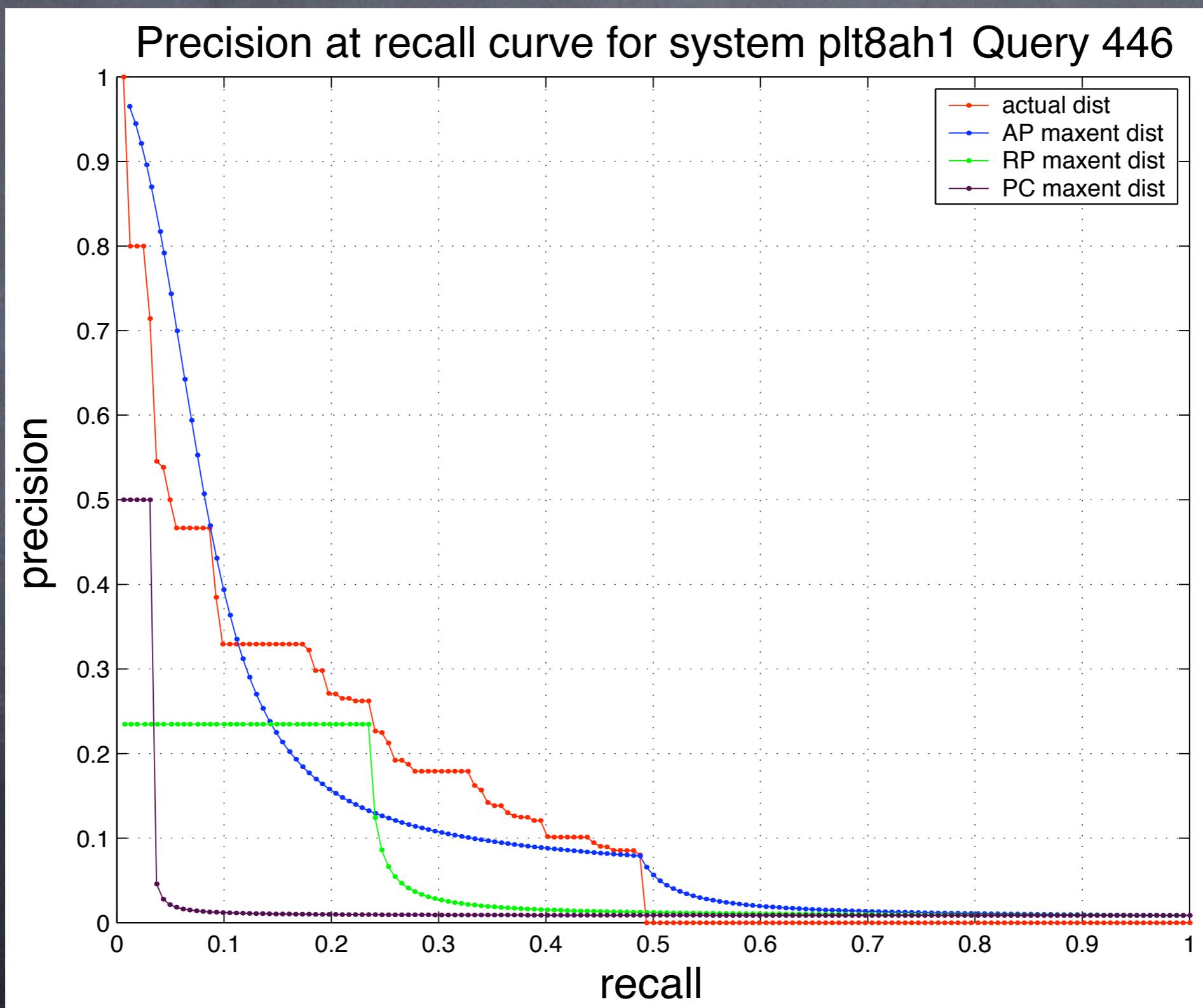
# P-R Curves



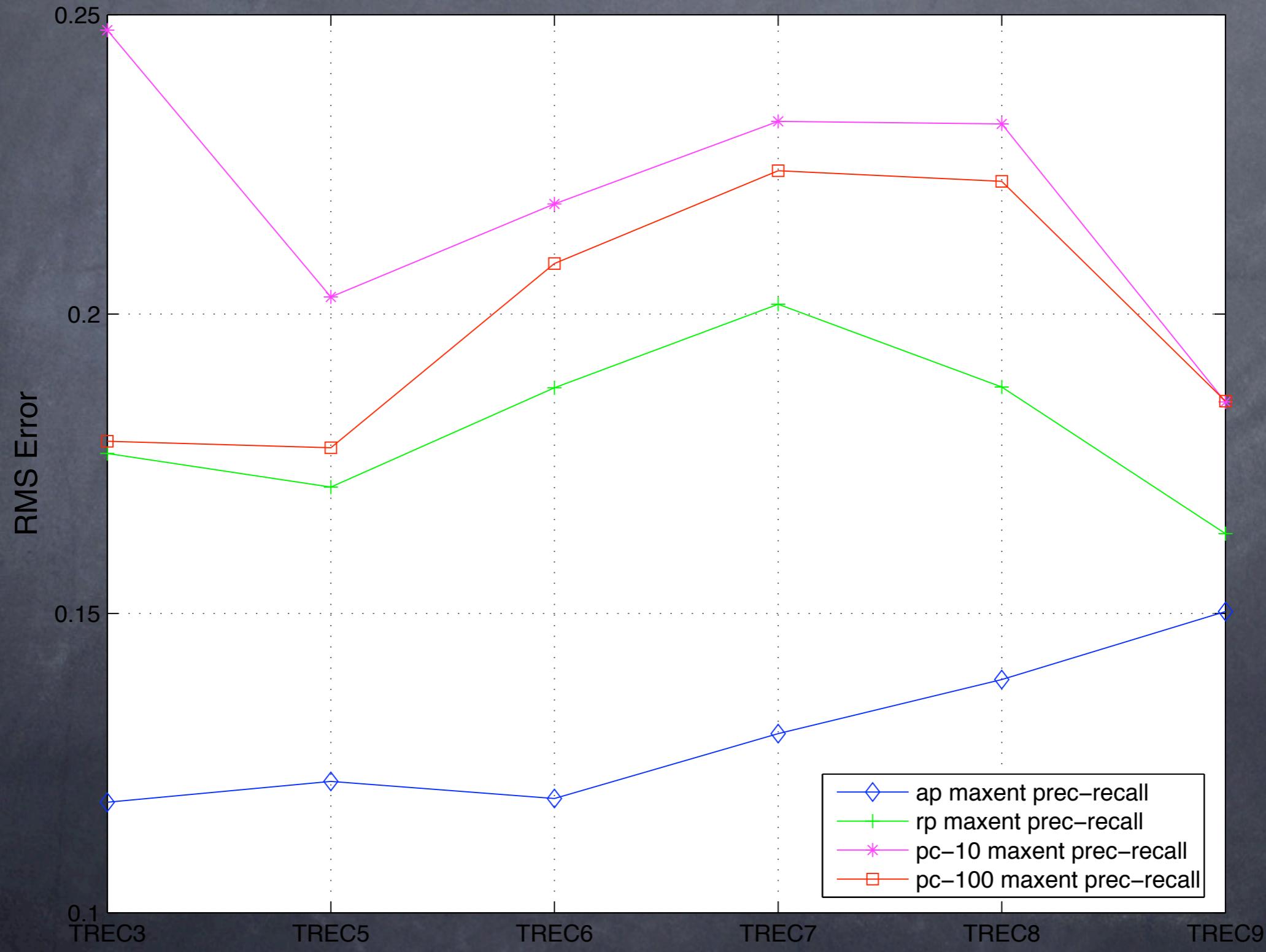
# P-R Curves



# P-R Curves



# Error



# Future Work & Questions?