Real-time Ranking of Electrical Feeders using Expert Advice

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Overview

- The problem
  - The electrical system
  - Available data
- Approach
- Challenges
- Our solution using Online learning
- Experimental results

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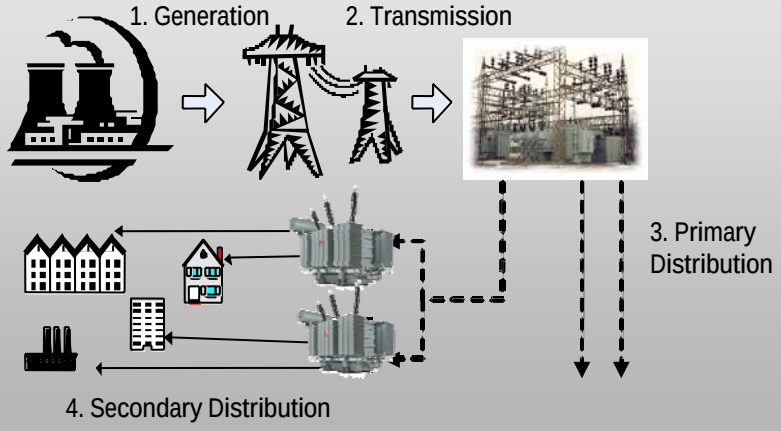
The Electrical System



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The Problem

- Distribution feeder failures result in automatic feeder **shutdown**
  - called “Open Autos” or O/As
- O/As **stress** networks, control centers, and field crews
- O/As are **expensive** ($ millions annually)
- Proactive replacement is much cheaper and safer than reactive repair
- How do we know which feeders to fix?

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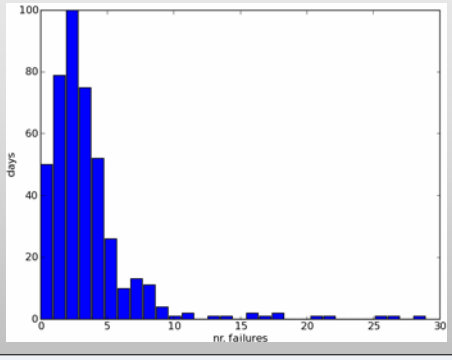
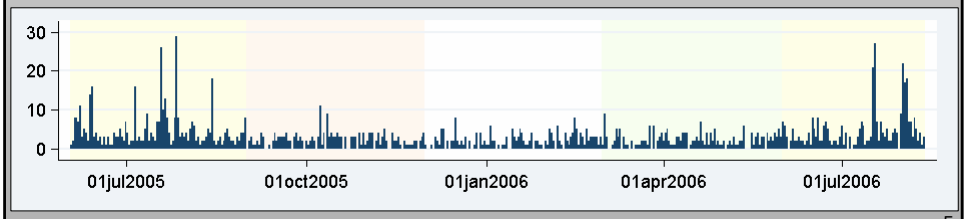
Some facts about feeders and failures

- mostly 0-5 failures per day
- more in the summer
- strong seasonality effects





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Feeder data

- **Static** data
  - Compositional/structural
  - Electrical
- **Dynamic** data
  - Outage history (updated daily)
  - Load measurements (updated every 15 minutes)
- Roughly **200** attributes for each feeder
  - New ones are still being added.

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Machine Learning Approach

- Leverage Con Edison's domain knowledge and resources
- Learn to rank feeders based on failure susceptibility
- How?
  - Assemble data
  - Train ranking model based on past data
  - Re-rank frequently using model on current data

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Feeder Ranking Application

- Goal: **rank** feeders according to failure susceptibility
  - High risk placed near the top
- Integrate different types of data
- Interface that reflects the latest state of the system
  - Update feeder ranking every 15 min.

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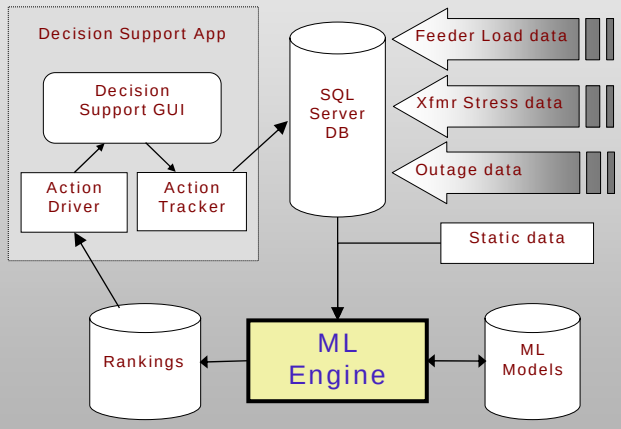
Application Structure



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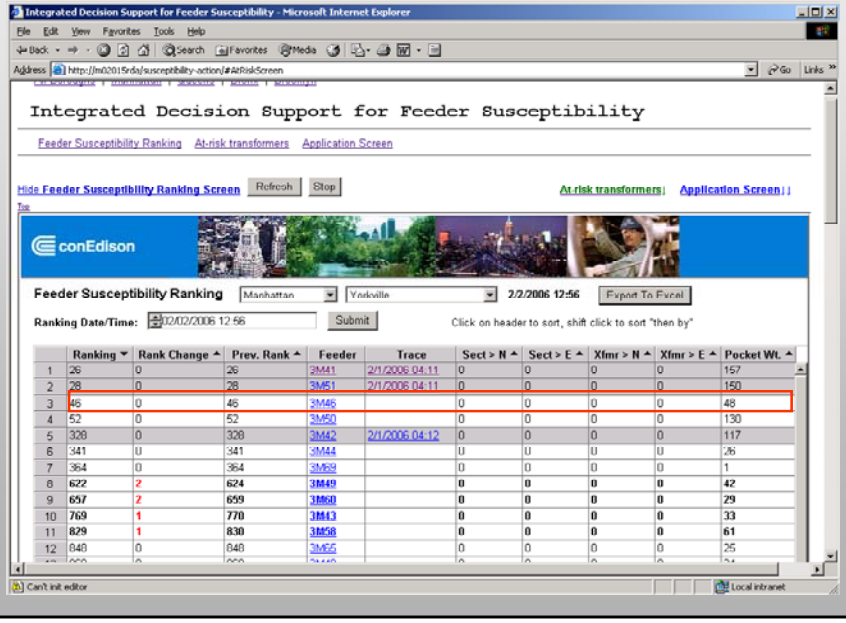
Decision Support GUI



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Simple Solution

- Supervised batch-learning algorithms
  - Use past data to train a model
  - Re-rank frequently using this model on current data
- Use the best performing learning algorithm
  - How do we measure performance?
  - MartiRank - boosting algorithm by [Long & Servedio, 2005]
    - Use MartiRank for dynamic feeder ranking

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Performance Metric

- Normalized **average rank of failed feeders**

$$1 - \frac{\sum_i rank(failure_i)}{\#failures * \#feeders}$$

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Performance Metric Example

$$1 - \frac{\sum_i rank(failure_i)}{\#failures * \#feeders}$$

$$1 - \frac{2+3+5}{3*8} = 0.5833$$

ranking	outages
1	0
2	1
3	1
4	0
5	1
6	0
7	0
8	0

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Real-time ranking with MartiRank

- MartiRank is a "**batch**" learning algorithm
- Deal with changing system by:
  - generating new datasets with latest data
  - Re-training new model, replacing old model
  - Using newest model to generate ranking
- Must implement "training strategies"

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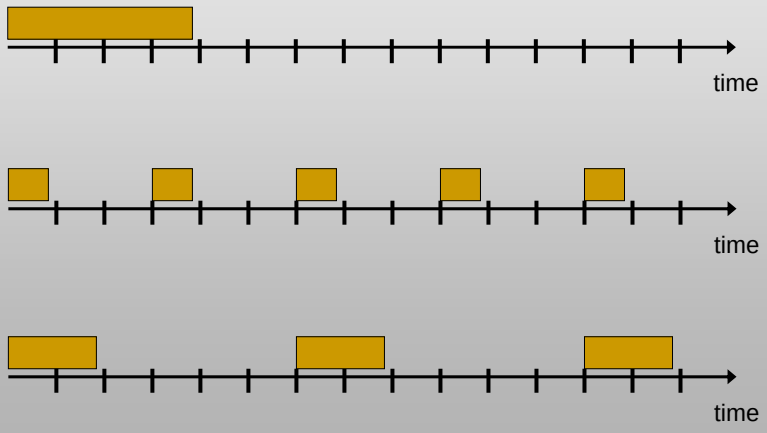
Real-time ranking with MartiRank



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How to measure performance over time

- Every ~15 minutes, generate new ranking based on current model and latest data
- Whenever there is a failure, look up its rank in the latest ranking before the failure
- After a whole day, compute normalized average rank

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Using MartiRank for real-time ranking of feeders

- MartiRank seems to work well, but..
  - User decides when to re-train
  - User decides how much data to use for re-training
  - Performance degrades over time
- Want to make system automatic
  - Do not discard all old models
  - Let the system decide which models to use

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Learning from expert advice

- Consider each model as an expert
- Each expert has associated weight
  - Reward/penalize experts with good/bad predictions
  - Weight is a measure of confidence in expert's prediction
- Predict using weighted average of top-scoring experts

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Learning from expert advice

- Advantages
  - Fully automatic
  - Adaptive
  - Can use many types of underlying learning algorithms
  - Good performance guarantees from learning theory: *performance never too far off from best expert in hindsight*
- Disadvantages
  - Computational cost: need to track many models "in parallel"

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Weighted Majority Algorithm [Littlestone & Warmuth '88]

- Introduced for binary classification
  - Experts make predictions in [0,1]
  - Obtain losses in [0,1]
- Pseudocode:
  - Learning rate as main parameter, ß in (0,1]
  - There are N "experts", initially weight is 1 for all
  - For t=1,2,3, …
    - Predict using weighted average of experts' prediction
    - Obtain "true" label; each expert incurs loss l_i
    - Update experts' weights using $w_{i,t+1} = w_{i,t} \cdot pow(ß,l_i)$

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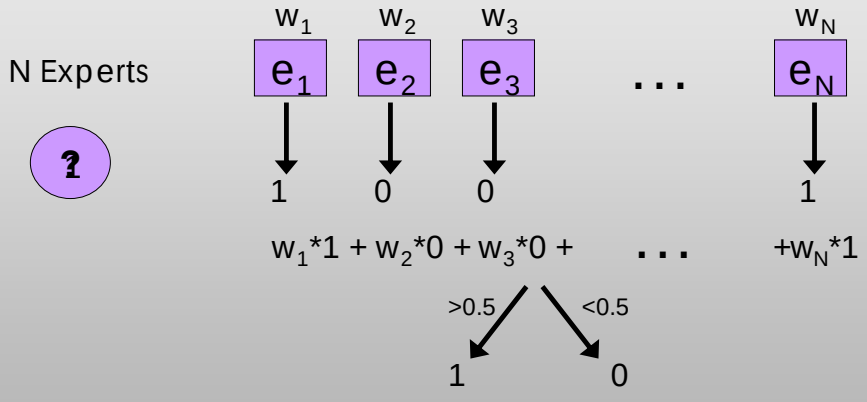
Weighted Majority Algorithm



- Calculate li = loss(i) for i=1,…,N
- Update: wi,t+1 = wi,t • pow(ß,li) for learning rate ß, time t and i=1,..,N

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In our case, can't use WM directly

- Use ranking as opposed to binary classification
- More importantly, do not have a fixed set of experts

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Dealing with ranking vs. binary classification

- Ranking loss as normalized average rank of failures as seen before, loss in [0,1]
- To combine rankings, use a weighted average of feeders' ranks

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Dealing with a moving set of experts

- Introduce new parameters
  - B: "budget" (max number of models) set to 100
  - p: new models weight percentile in [0,100]
  - α: age penalty in (0,1]
- If too many models (more than B), drop models with poor q-score, where
  - $q_i = w_i \bullet pow(\alpha, age_i)$
  - I.e., α is rate of exponential decay

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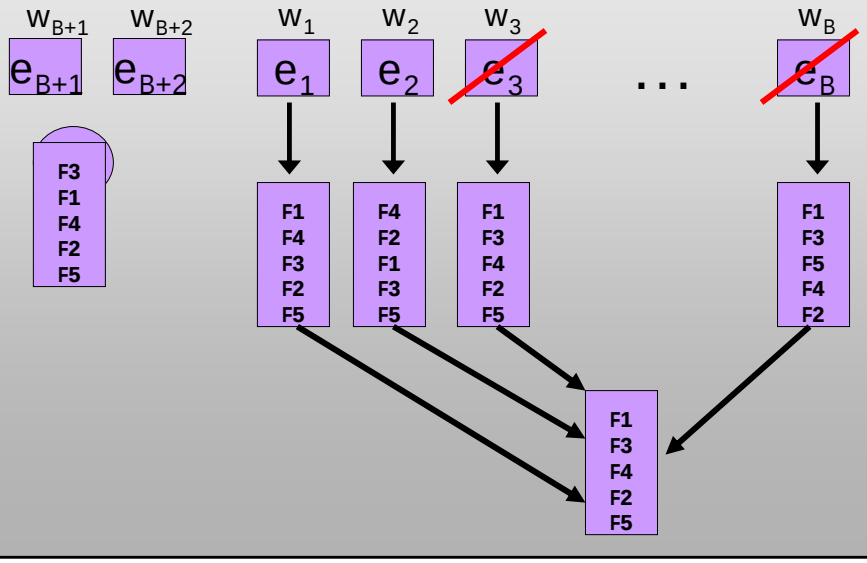
Online Ranking Algorithm



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Other parameters

- How often do we train and add new models?
  - Hand-tuned over the course of the summer
  - Alternatively, one could train when observed performance drops .. not used yet
- How much data do we use to train models?
  - Based on observed performance and early experiments
    - 1 week worth of data, and
    - 2 weeks worth of data

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Experimental Comparison

- Compare our approach to
  - Using "batch"-trained models
  - Other online learning methods
- Ranking Perceptron
  - Online version
- Hand Picked Model
  - Tuned by humans with domain knowledge

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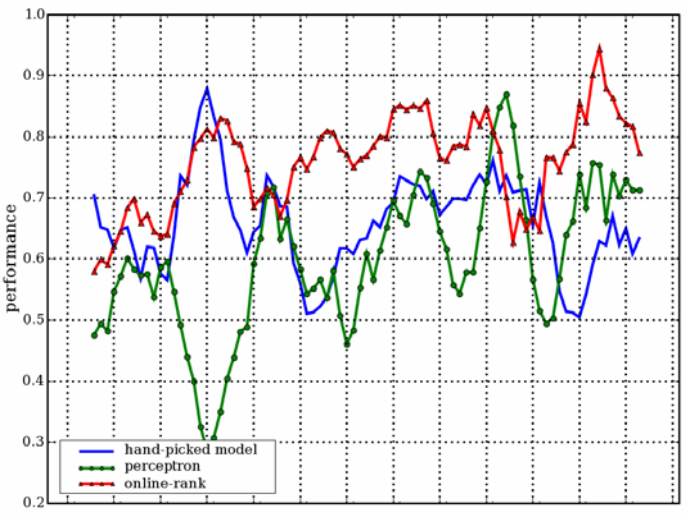
Performance – Summer 2005



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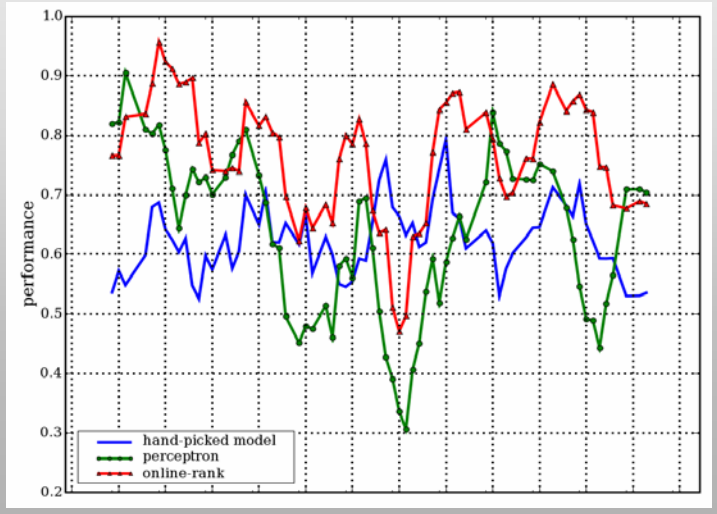
Performance – Winter 2006



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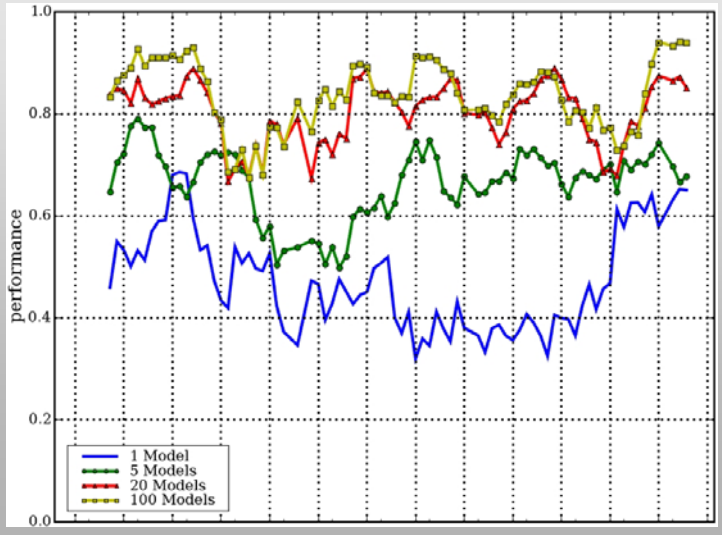
Parameter Variation - Budget



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Future Work

- Concept drift detection
  - Add new models only when change is detected
- Ensemble diversity control
- Exploit re-occurring contexts

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