CS 147:
Computer Systems Performance Analysis
Workload Characterization

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Overview

Terminology

Specifying Parameters

Identifying Parameters
- Histograms
- Principal-Component Analysis
- Markov Models

Clustering
- Clustering Steps
- Clustering Methods
- Using Clustering

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Workload Characterization Terminology

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- Fit probability distribution to shape of histogram
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- Use 3-D plotting package to show 2 parameters
  - Or plot each datum as 2-D point and look for “black spots”
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Principal-Component Analysis (PCA)

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- Could plot endless pairs
  - Still might not show complex relationships
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  - Rotates parameter set to align with axes
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- Requests come in sequences
- Sequencing affects performance
- Example: disk bottleneck
  - Suppose jobs need 1 disk access per CPU slice
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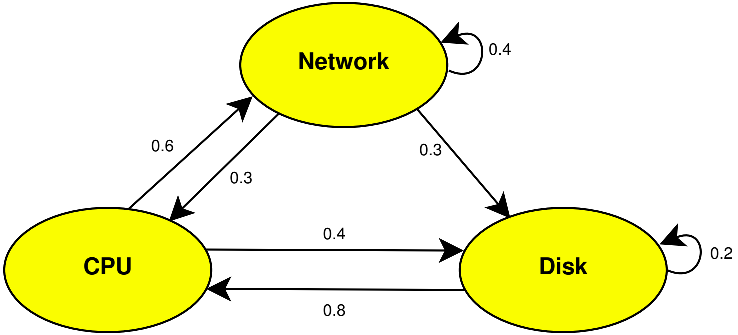
Introduction to Markov Models

- Represent model as state diagram
- Probabilistic transitions between states
- Requests generated on transitions



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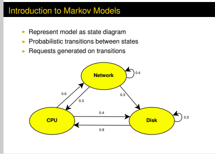
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- Use matrix to count pairs of states
- Normalize rows to sum to 1.0

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CPU		0.6	0.4
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Example Markov Model

- Reference string of opens, reads, closes: ORORRCOORCRRRRCC
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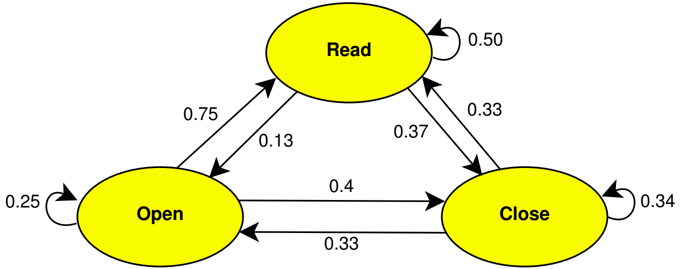
Markov Model for I/O String

- Divide each row by its sum to get transition matrix:

	Open	Read	Close
Open	0.25	0.75	
Read	0.13	0.50	0.37
Close	0.33	0.33	0.34

- Model:



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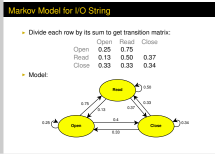
CS147
Identifying Parameters
Markov Models
Markov Model for I/O String



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- Often useful to break workload into categories
- "Canonical example" of each category can be used to represent all samples
- If many samples, generating categories is difficult
- Solution: clustering algorithms

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Steps in Clustering

- Select sample
- Choose and transform parameters
- Drop outliers
- Scale observations
- Choose distance measure
- Do clustering
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- Can test sample after clustering: does every observation fit into some cluster?
- Sampling options
  - Random
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- Goal is to limit complexity of problem
- Concentrate on parameters with high impact, high variance
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  - Drop a parameter, re-cluster, see if different
- Consider transformations such as Sec. 15.4 (logarithms, etc.)

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- Must get rid of observations that would skew results
  - Need great judgment here
  - No firm guidelines
- Drop things that you know are “unusual”
- Keep things that consume major resources
  - E.g., daily backups

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Scaling Observations

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- Options:
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  - Weight based on importance or variance
  - Normalize range to [0, 1]
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Chi-square distance is:

$$d = \sum_{k=1}^{n} \left\{ \frac{(x_{ik} - x_{jk})^2}{x_{ik}} \right\}$$

and requires $x_{\cdot k}$ to be close together or low values of $x_{\cdot k}$ will over-weight parameters. Used primarily in distribution fitting.

Clustering Methods

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- Repeat until single cluster:
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  - Find smallest distance
  - Merge clusters with smallest distance
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- Method produces stable results
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- First randomly assign points to clusters
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- Start with each point in own cluster
- For each point, make list of *n* closest other points
- For each point pair, if *k* of *n* nearest neighbors are shared, combine their clusters
- Finds non-globular clusters
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- Humans will often see patterns where computer sees none
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