### Finding a "Kneedle" in a Haystack: Detecting Knee Points in System Behavior



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#### Background

- First noticed problem back in 2006 when building a distributed application management framework (USENIX 2006)
- Needed a way to cope with stragglers in distributed computations



# **Dealing with Stragglers**

- Detect slow and/or failed machines (that finish after knee)
- Continue computation without stragglers
- Reallocate work as needed



### **Related Problems**

- "One of the common causes that lengthens the total time taken for a MapReduce operation is a "straggler": a machine that takes an unusually long time to complete one of the last few map or reduce tasks in the computation." – Dean & Ghemawat, 2004
- "If the load is small, throughput generally keeps up with the load. As the load increases, throughput increases. After the load reaches the network capacity, throughput stops increasing. This point is called the knee." – Jain, 1990

## **Related Problems**

 "As each of the graphs in the figure shows, when the query load increases, we notice a sharp 'knee' in the curves beyond which the success rate drops sharply and delays increase rapidly."

- Chawathe et al, 2003

- "For the purpose of determining the thresholds of a coarse-grained policy, the **knee** points on the curve of object popularity-to-size ratios may serve as good candidates."
  - Zhong et al, 2008





## Problem Statement

- What is a knee?
  - For simplicity, we assume "elbows" are equivalent to knees (via a trivial conversion)
- Can we develop a general purpose knee detection algorithm that does not require tuning for a specific system and is applicable in a wide range of settings?

## Outline

- Background and motivation
- Problem statement
- Our approach
  - Defining knees
  - Detecting knees
- Results and evaluation
  - Synthetic and real data
  - Online and offline scenarios
- Conclusion

# Defining Continuous Knees

- For continuous functions:
  - Knees = points of maximum curvature
  - Curvature based on first and second derivative

$$K_f(x) = \frac{f''(x)}{\left(1 + f'(x)^2\right)^{1.5}}$$

### **Defining Continuous Knees**

- For CDF of Gaussian with mean=0 and std dev=1, max K<sub>f</sub>(x) occurs at x ≈ 1.
- Note: Inflection point occurs at x = 0, which is not the knee!



Simplex 2011

### Limitations

- Problems with max curvature:
  - Data is often discrete and non-continuous
  - Data is not easily fit to a single continuous function
  - Max curvature can occur outside of data range
  - Does not work well in real-time/online scenarios
- How do we detect knees in discrete data?

### Kneedle

- Our "Kneedle" algorithm approximates points of maximum curvature in discrete data
- Identifies points where data differs the most from a flat line
- Works in online and offline settings

- I. Use smoothing spline to fit data to smooth curve while preserving original shape.
- 2. Normalize points to unit square.



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## **Evaluation Summary**

- Used synthetic and real data
  - Synthetic data set based on a Gaussian CDF; allows us to approximate "true knees" based on curvature equation
  - Real data extracted from graphs in published papers; extracted from real systems
- Tested in online and offline scenarios
  - Online "real-time" data taken from running systems
  - Offline all data points are known in advance

## **Evaluation Summary**

- Metrics of interest:
  - Online scenarios latency of detection
  - Offline scenarios accuracy, precision, and recall
- Compared against other knee-finding algorithms
  - Online scenarios EWMA
  - Offline scenarios Menger, Angle-based

#### **Overall Performance**



# Offline Accuracy – Synthetic Data

- F-Score is harmonic mean of precision and recall
  - Captures correctness and completeness of knees
  - F-Score of I is best
- Evaluated against true knees



## Offline Accuracy – Synthetic Data

Difference
between detected
and true knees



#### Sensitivity Parameter



#### **Online Detection Latency**

 How long (in number of points) does it take to detect knees



#### Offline Analysis – Real Data

 Detect knees in real published data

• Data source:

M. Zhong, K. Shen, and J. Seiferas, "Replication Degree Customization for High Availability," in EuroSys, 2008.



### Online Analysis – Real Data

 Reallocate work in MapReduce-like batch scheduler running on PlanetLab



#### Online Analysis – Real Data

 Determine TCPfriendly sending rate in streaming application



## Conclusion

- Contributions
  - Presented formal definition of a knee
  - Described Kneedle, an algorithm for finding knee points in offline and online scenarios
  - Evaluated Kneedle in a variety of settings
  - Integrated Kneedle into existing applications with minimal effort

# Thanks!

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