Exploring KC models in DataShop: with a side of clustering and AFM

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Mentors: Nan Li and Zach Pardos

Problem Statement

- Human Built KC Models Require Effort
- PCA Built KC Models are Hard to Interpret
- I wanted Interpretable KC Models more Efficiently

Data Specific Solution

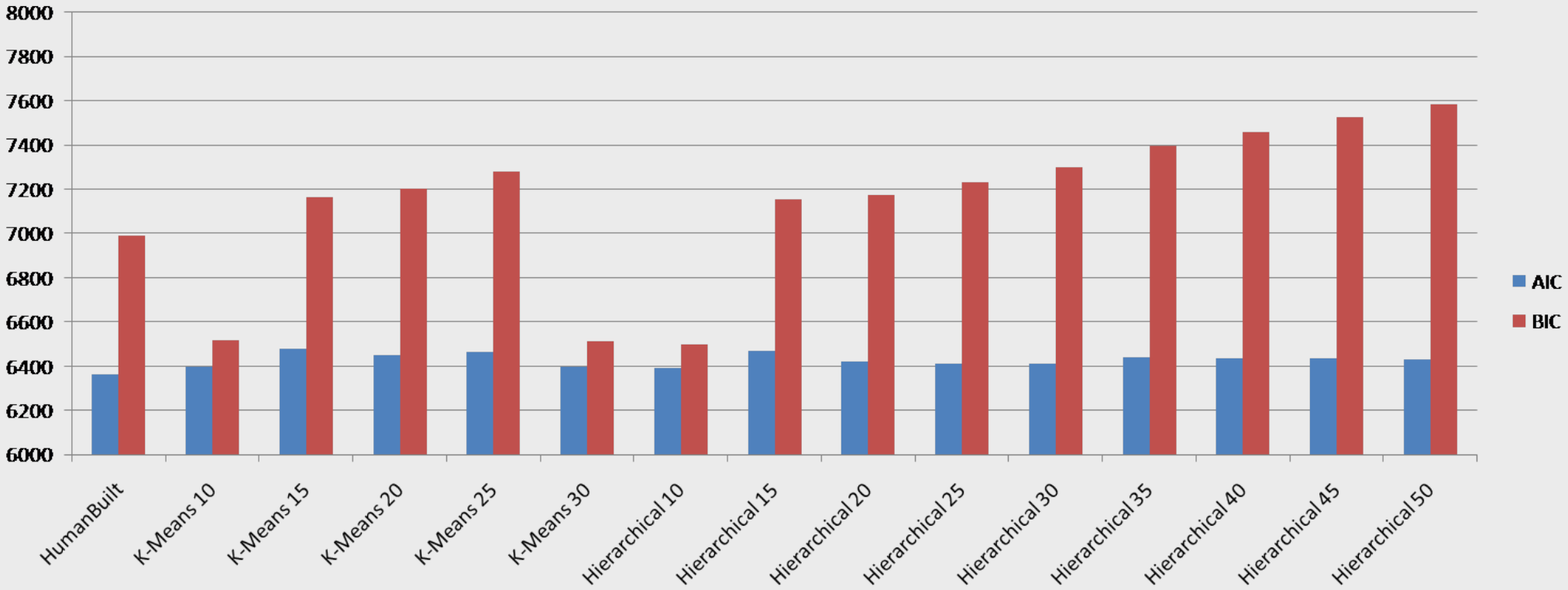
Algebra Dataset example: -4y + 8 = (3/x) … not too general

- Convert to simplified form: : -nv + n = (n/v)
- Look for Unigrams, Bigrams & Trigrams eg: -, -n, -nv
- Create Binary Matrix of which problems include which unigrams, bigrams, & trigrams

	n	nv	-n	(n	+n=
-4y + 8 = (3/x)	1	1	1	1	1
x = 7/8 – 1	1	0	1	0	0
6 + 1 = y/8 * 4	1	0	0	0	1
9/(-4x) = 9 + x/3	1	1	1	0	0
y/6 = 9/6	1	0	0	0	0

- Run Cluster Analysis on that Binary Matrix
- Use Clusters as KC Model

Qualified Success



Cluster/KC	1	3	12	13	18
Follows Form	n=n/v	n/v*v=nv	n/n=nv/n (often common denominator)	v=n/n	(-nv) No other *,/,or v in equation

Philosophy and Future Work

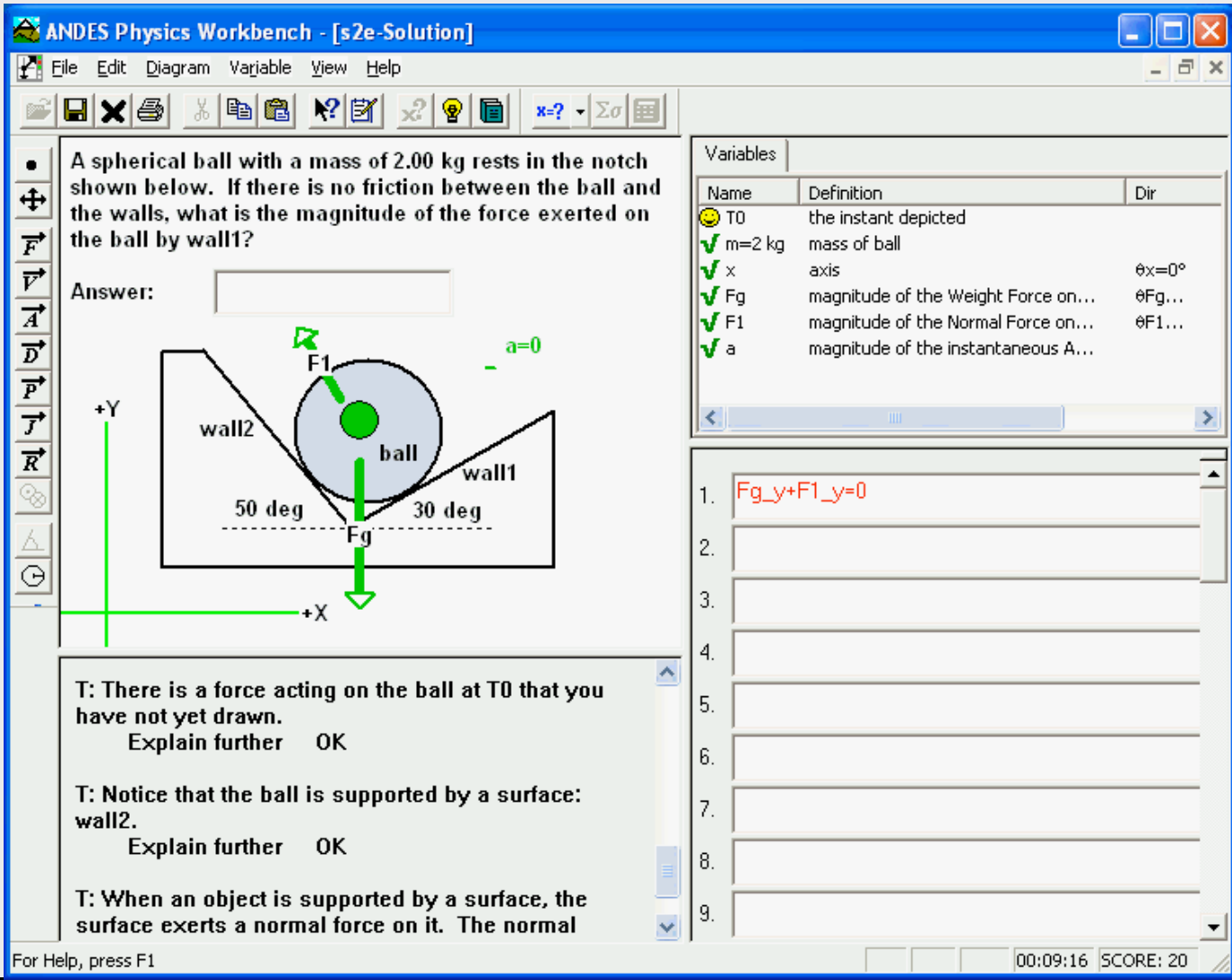
- Synthesis: Apply LFA to Use Best of Each KC Model
- Extension:
  - Target areas where human judgment doesn't perform well
  - Apply automated methods to fill those gaps
- Proposed Future Work
  - Find KCs which perform "badly"
  - Apply PCA to that subset

Acknowledgements

- Thanks to Ken Koedinger who suggested the idea of generating KC models from clustered ngrams
- Thanks to mentors Nan Li and Zach Pardos whose help made this project possible
- Thanks to CMU's LearnLab and DataShop for providing tools to facilitate these analyses and a vibrant learning environment

Exploring Physics KCs for the Andes tutor

- Andes is an intelligent tutor system designed to help students with physics homework: USNA Physics - Fall 2008, Fall 2009
- Hands on tutor that takes students through all problem solving steps
- Majority of the Andes data sets have not been analyzed, and models depend on tasks
- Attempted to add physics information extracted from step and problem names



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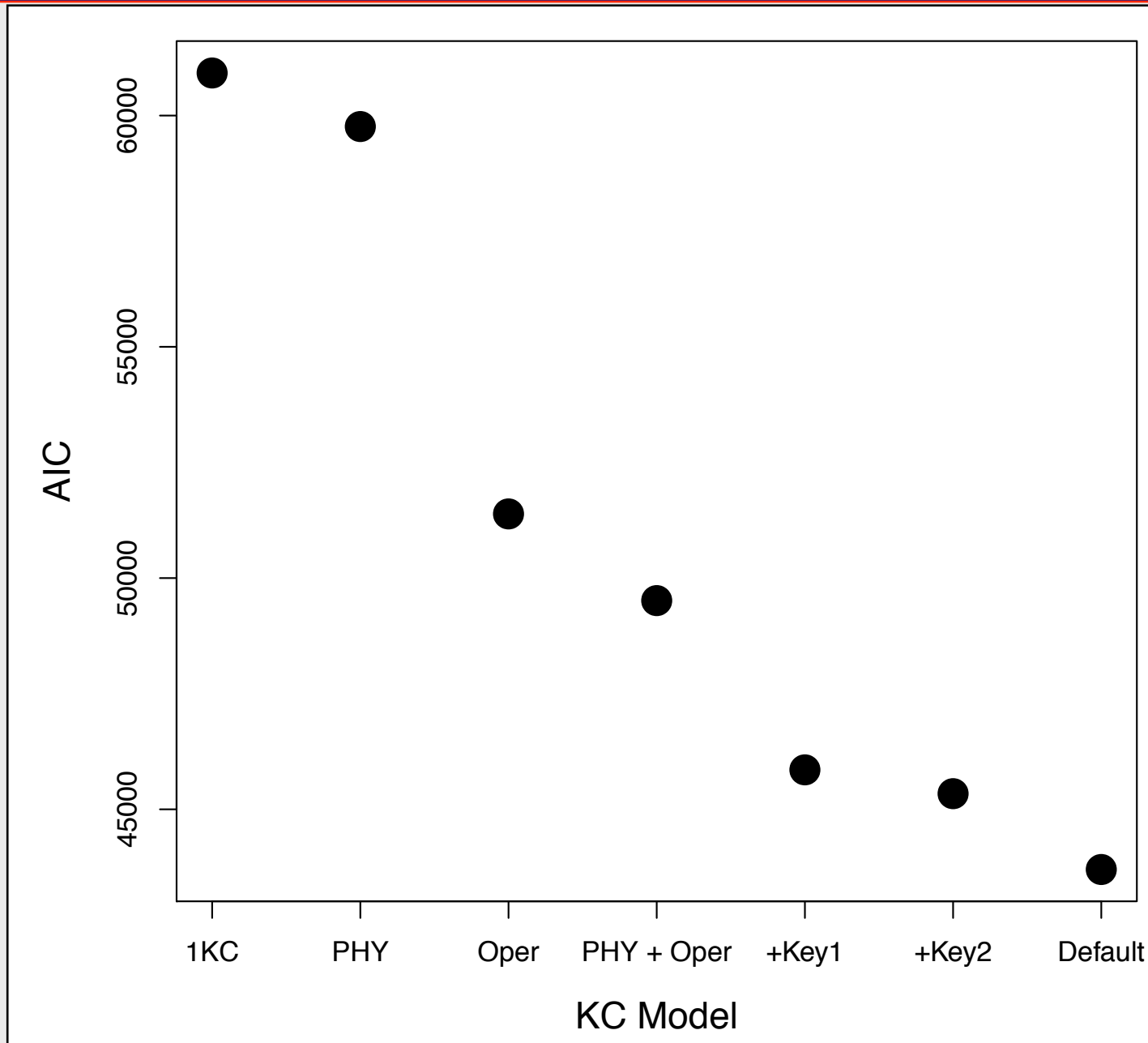
Exploring Physics KCs for the Andes tutor

1KC:	Single KC
PHY:	by physics topic
Oper	Andes task (not step)
PHY+ Oper	concatenate two above
Oper +Key1	refine Oper with Key1
Oper +Key2	refine Oper with Key2
Default	Tasks and physics



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Exploring the Additive Factor Model (AFM)

- Interested in finding ways to incorporate time-based features into predictions of learning
- AFM is in a class of logistic regression techniques widely used in educational prediction (was great to get some valuable experience!)

$$\ln\left(\frac{p_{ij}}{1-p_{ij}}\right) = \theta_i + \sum_{k=1}^{K} q_{jk}\beta_k + \sum_{k=1}^{K} q_{jk}\gamma_k T_{ik}$$

- Adjusted AFM in the R language to include time-based features, and explored the outcomes of the prediction

Koeding, McLaughlin, & Stamper (2012)
Cen, Koedinger, & Junker (2006)

Exploring the Additive Factor Model (AFM)

- Geometry96-97 DataShop data set
- Included duration feature (time in sec)
- Also investigated ways of discretizing time

Model	AIC
AFM	5084.1
AFM + time	5082.0
AFM + KC:time	5083.8

- Time in this context does not make large differences. Will continue to investigate, including how best to incorporate various time measures into such models.

Thanks! and Future Work

- Future work:
  - Prepare online course data from MIT for DataShop
  - Continue exploring AFM and logistic regression models

- Thanks to Ken Koedinger and Nan Li for access to AFM model exploration code in R!!!

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Given:
p_{ij} = probability student i gets step j correct
Q_{kj} = knowledge component k needed for step j
T_{ik} = opportunities student i has had to practice k
Estimated:
θ_i = proficiency of student i
β_k = difficulty of KC k
γ_k = gain for each practice opportunity on KC k

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