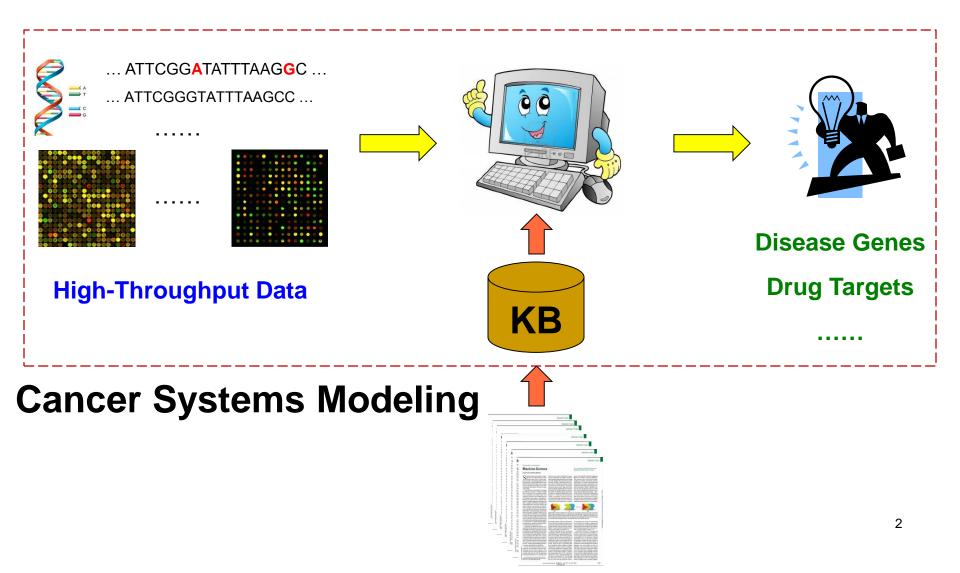


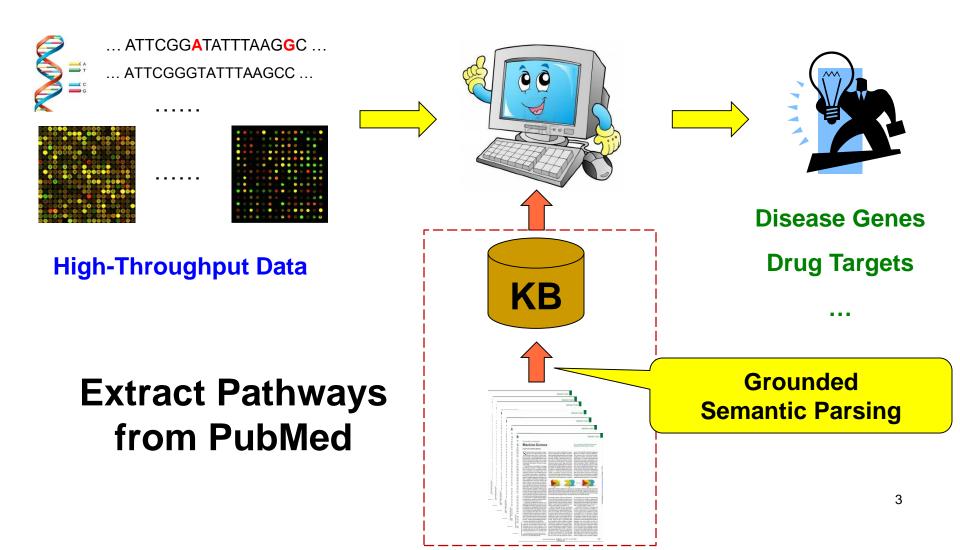
Machine Reading for Cancer Panomics

Hoifung Poon

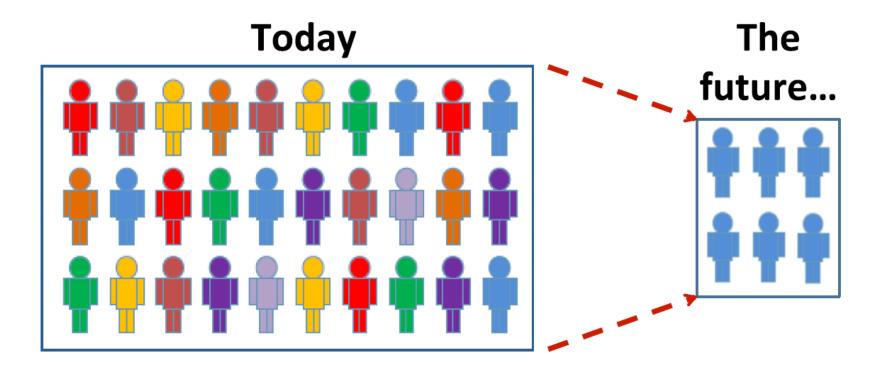
Overview



Overview



Precision Medicine



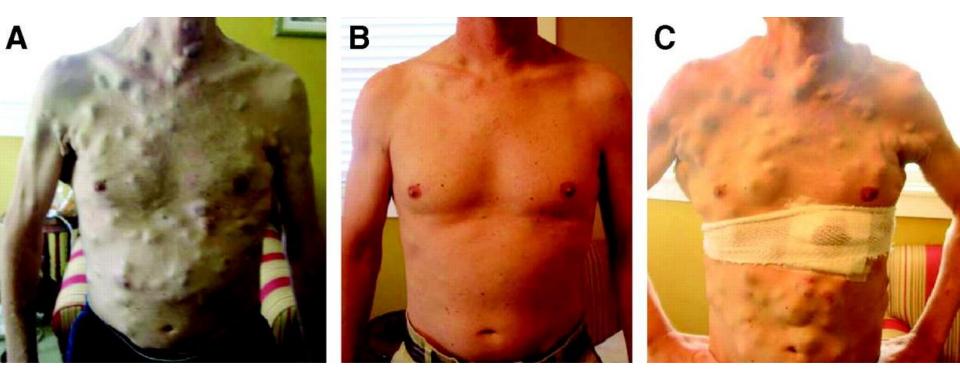
Vemurafenib on BRAF-V600 Melanoma



Before Treatment

15 Weeks

Vemurafenib on BRAF-V600 Melanoma

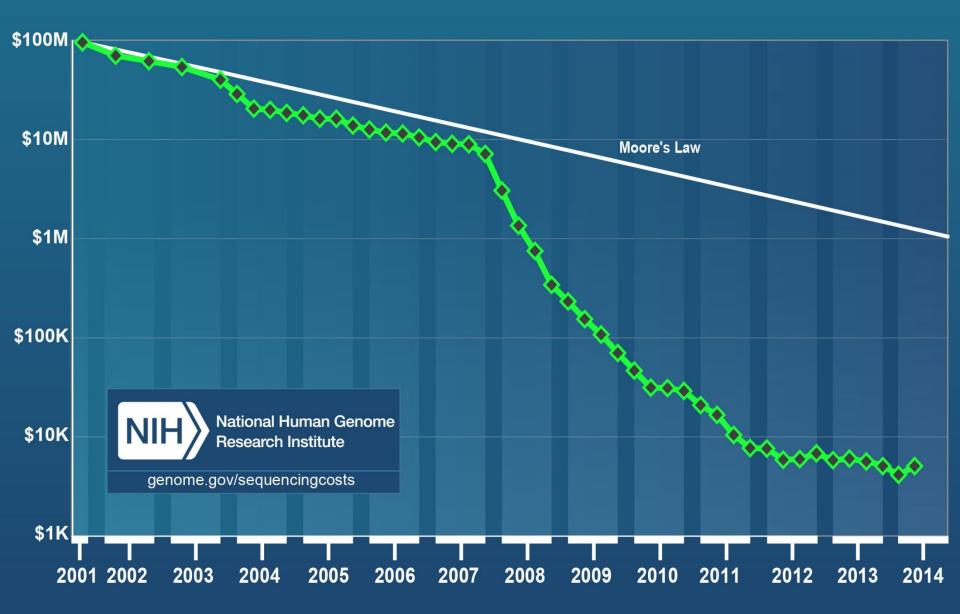


Before Treatment

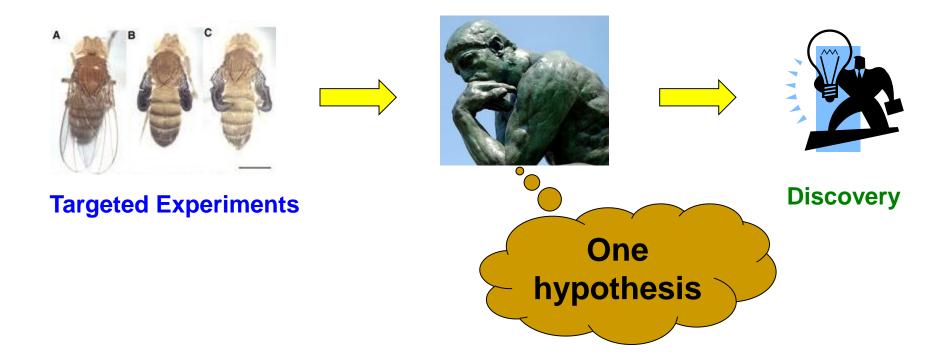
15 Weeks

23 Weeks

Cost per Genome



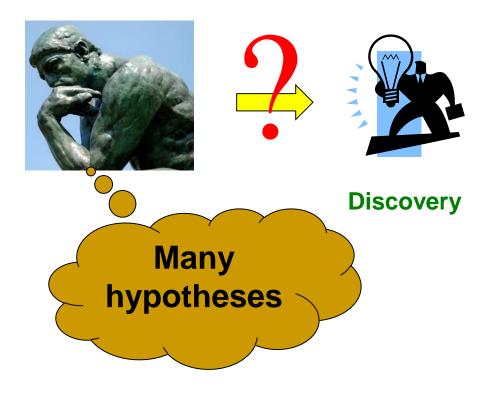
Traditional Biology



Genomics



High-Throughput Experiments



Genome-Wide Association Studies (GWAS)







"Genetic diagnosis of diseases would be accomplished **in 10 years** and that treatments would start to roll out perhaps five years after that."



"A Decade Later, Genetic Maps Yield Few New Cures" New York Times, June 2010.

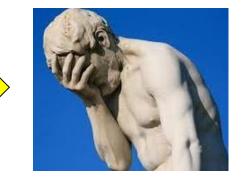
Key Challenges

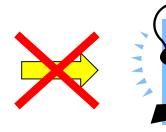
- Human genome: 3 billion base pairs
- Potential variations: > 10 million variants
- Combination: $> 10^{1000000}$ (1 million zeros)
- Machine learning problem
 - Atomic features: > 10 million
 - Feature combination: Too many to enumerate

Genomics



High-Throughput Experiments





Discovery

How to Scale Discovery?

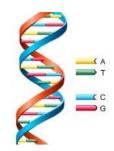
Cancer

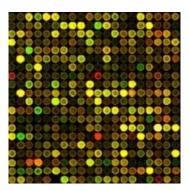


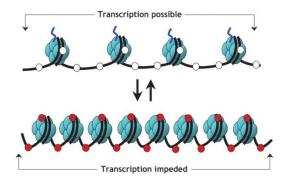
- Hundreds of mutations
- Most are "passenger", not driver
- Can we identify likely drivers?

Panomics

... ATTCGGATATTTAAGGC ...







Genome

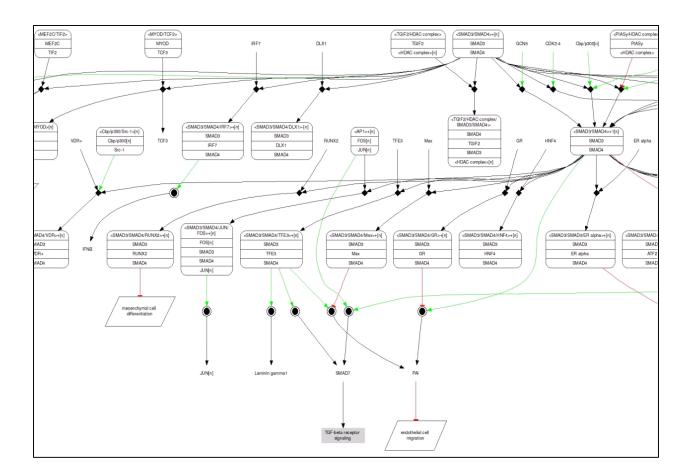
Transcriptome

Epigenome

.....

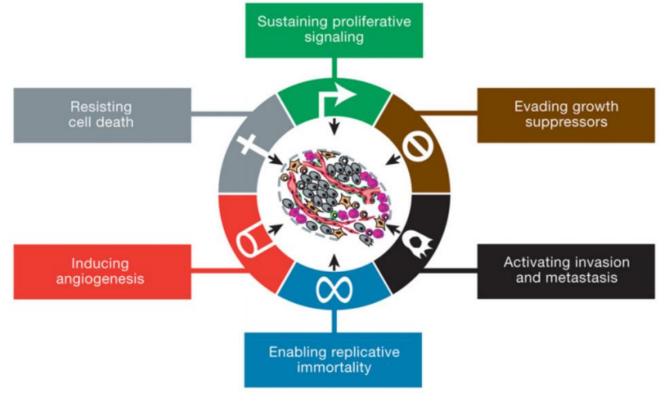
Pathway Knowledge

Genes work synergistically in pathways



Why Hard to Identify Drivers?

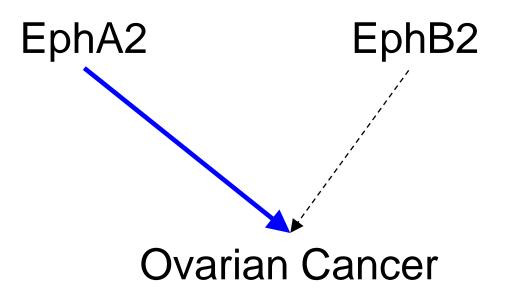
Complex diseases ← Perturb multiple pathways



Hanahan & Weinberg [Cell 2011]

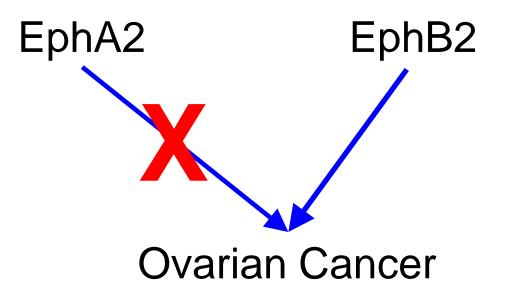
Why Cancer Comes Back?

- Subtypes with alternative pathway profile
- Compensatory pathways can be activated

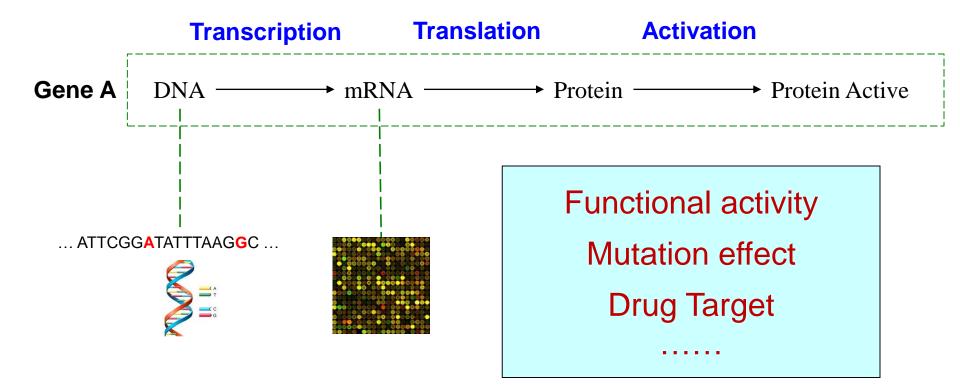


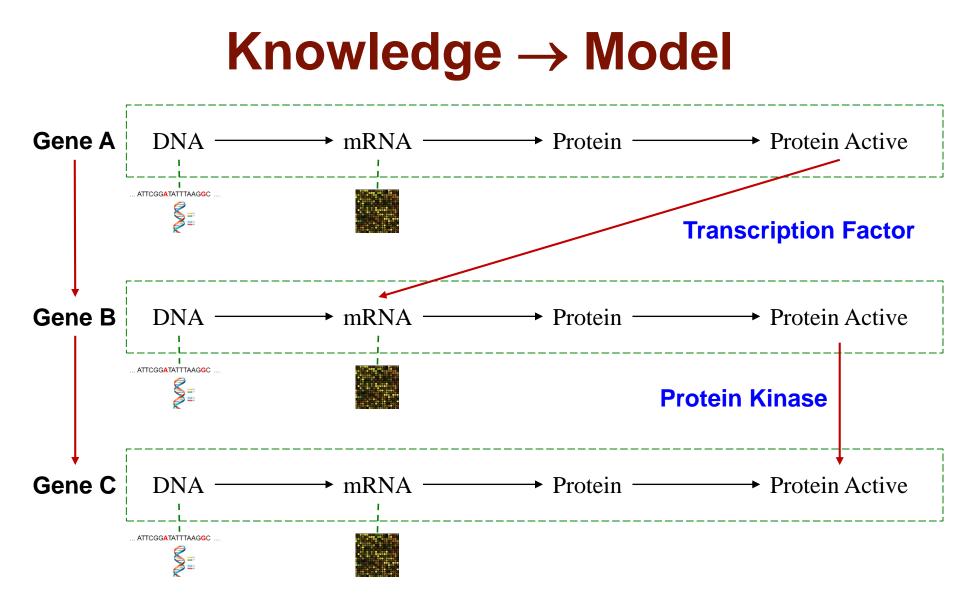
Why Cancer Comes Back?

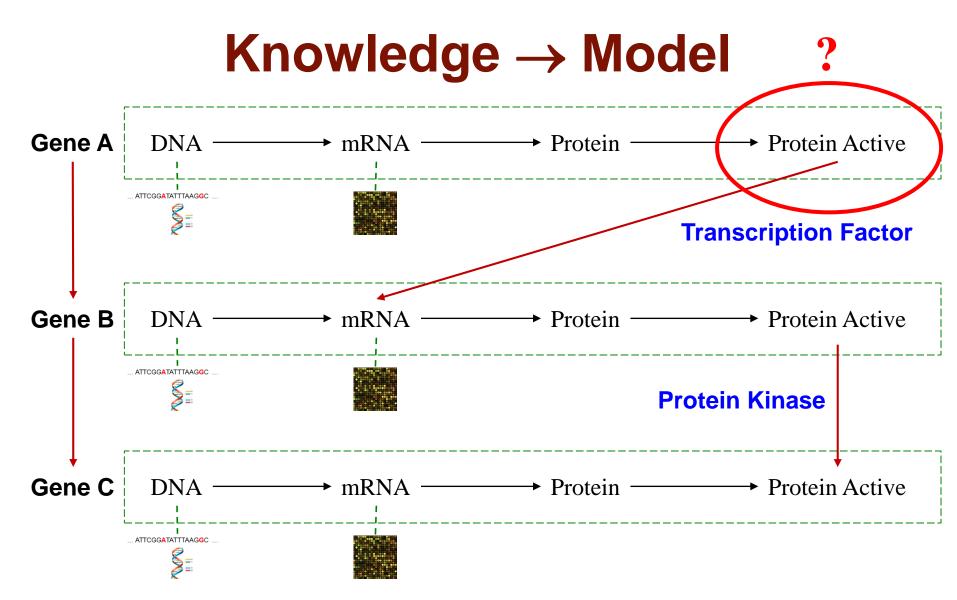
- Subtypes with alternative pathway profile
- Compensatory pathways can be activated

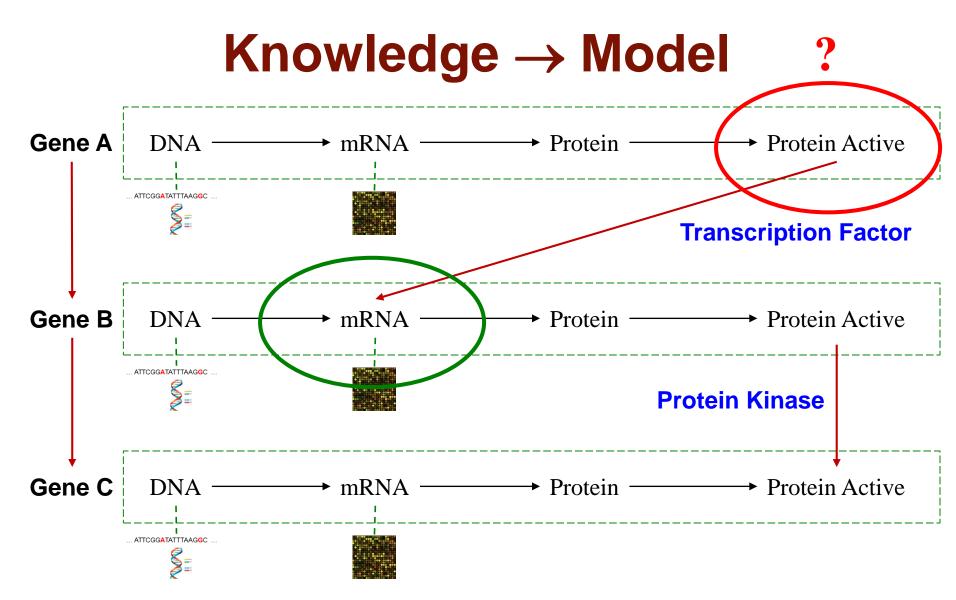


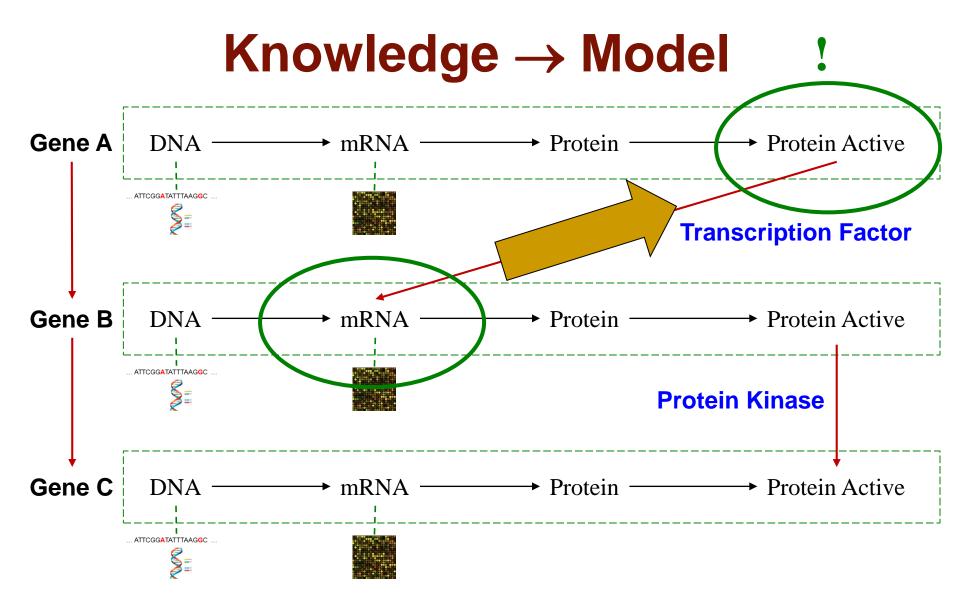
Cancer Systems Modeling



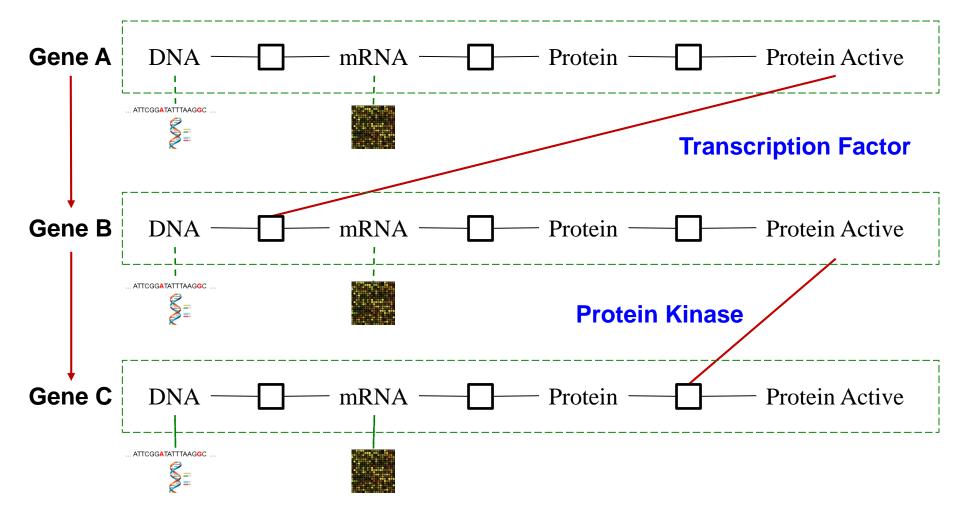




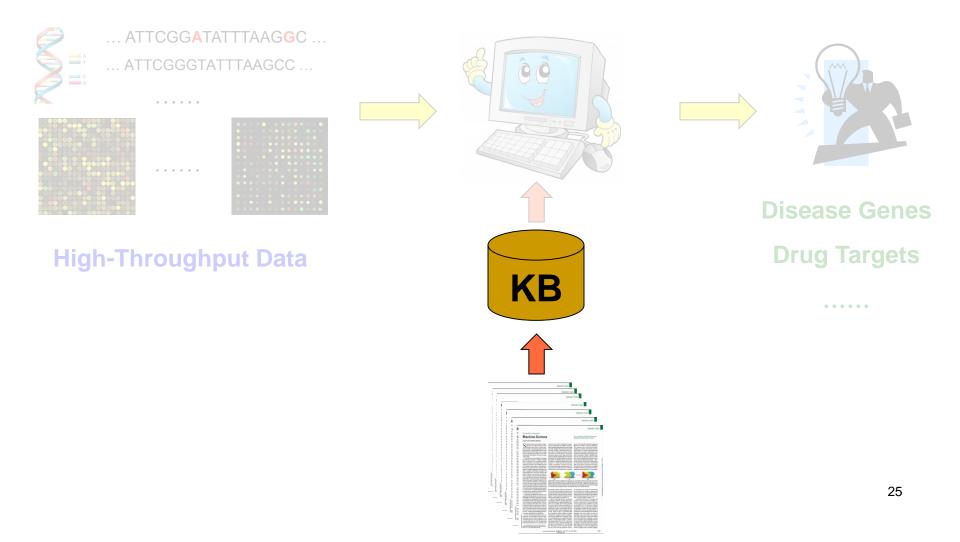




Approach: Graph HMM

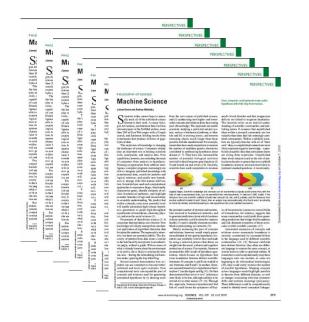


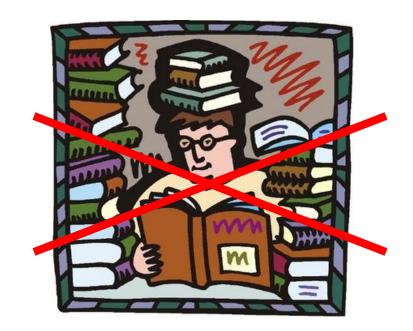
Extract Pathways from PubMed

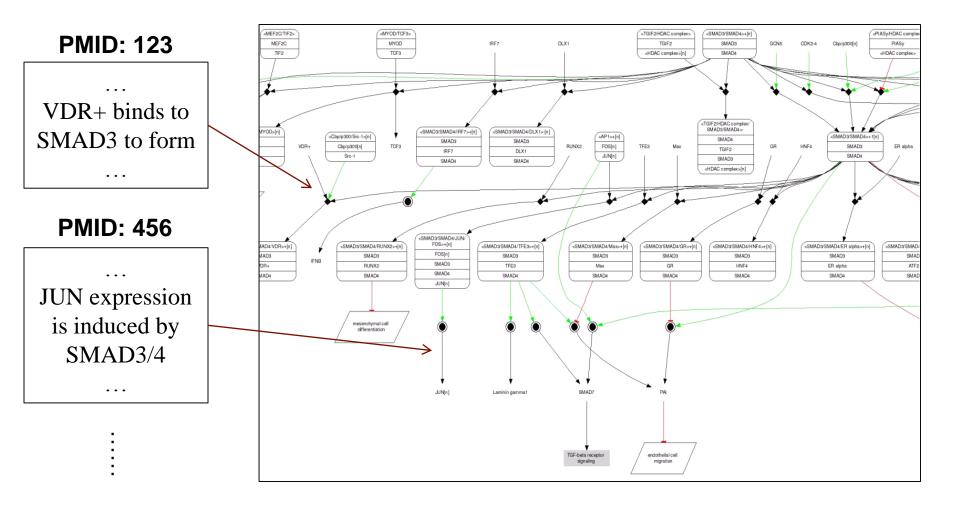


PubMed

- 24 millions abstracts
- Two new abstracts every minute
- Adds over one million every year





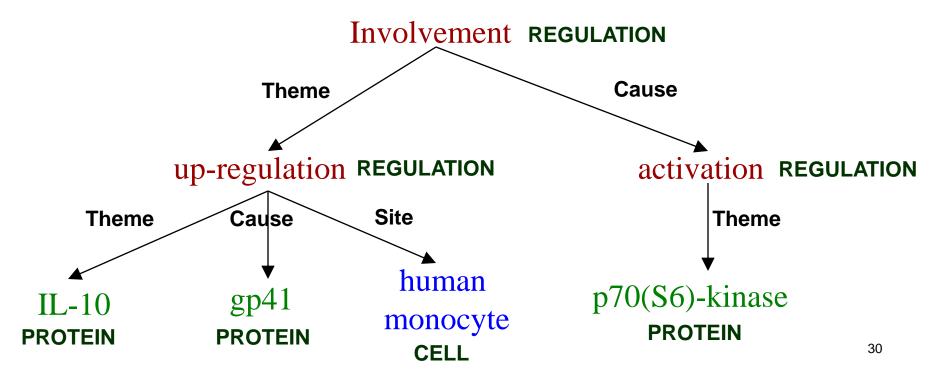


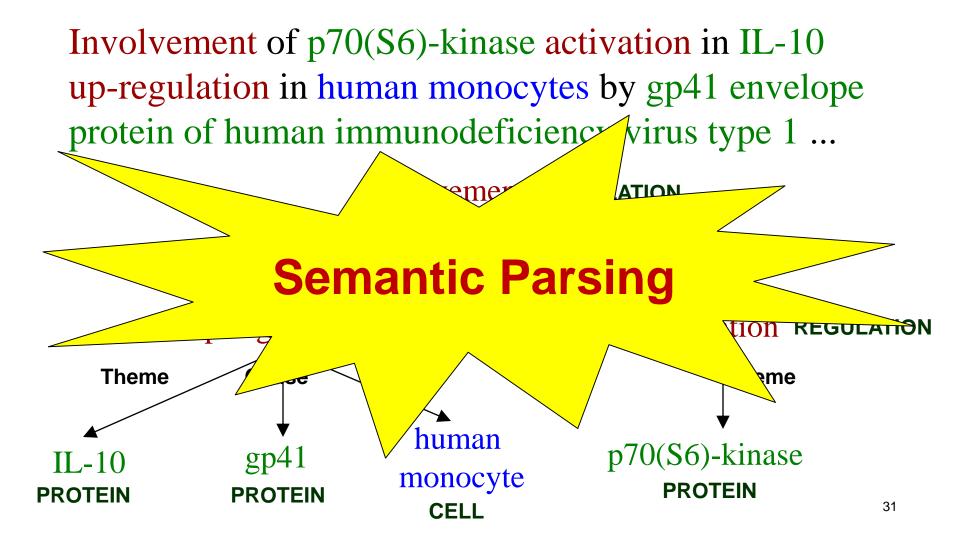
Involvement of p70(S6)-kinase activation in IL-10 up-regulation in human monocytes by gp41 envelope protein of human immunodeficiency virus type 1 ...

Involvement of p70(S6)-kinase activation in IL-10 up-regulation in human monocytes by gp41 envelope protein of human immunodeficiency virus type 1 ...

IL-10gp41humanp70(S6)-kinasePROTEINPROTEINCELLPROTEIN

Involvement of p70(S6)-kinase activation in IL-10 up-regulation in human monocytes by gp41 envelope protein of human immunodeficiency virus type 1 ...





Long Tail of Variations

TP53 inhibits BCL2.

Tumor suppressor P53 down-regulates the activity of BCL-2 proteins. BCL2 transcription is suppressed by P53 expression. The inhibition of B-cell CLL/Lymphoma 2 expression by TP53 ...

• • • • • •

Bottleneck: Annotated Examples

- GENIA (BioNLP Shared Task 2009-2013)
 - 1999 abstracts
 - MeSH: human, blood cell, transcription factor
- Challenge for "supervised" machine learning
- Can we breach this bottleneck?

Free Lunch #1: Distributional Similarity

- Similar context \rightarrow Probably similar meaning
- Annotation as latent variables
 Textual expression → Recursive clusters
- Unsupervised semantic parsing

Poon & Domingos, "Unsupervised Semantic Parsing". EMNLP 2009. **Best Paper Award**.

Recursive Clustering

TP53 inhibits BCL2.

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• • • • • •

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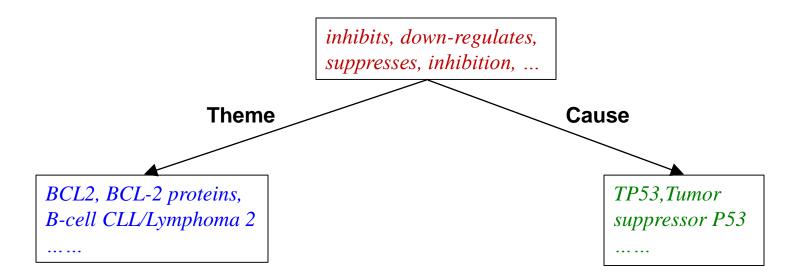
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Recursive Clustering

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Free Lunch #2: Existing KBs

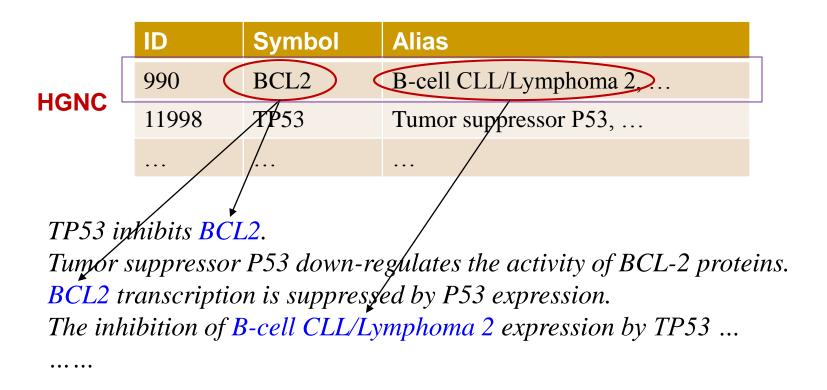
- Many KBs available
 - Gene/Protein: GeneBank, UniProt, ...
 - Pathways: NCI, Reactome, KEGG, BioCarta, ...
- Annotation as latent variables
 Textual expression → Table, column, join, ...
- Grounded semantic parsing

Entity Extraction

| | ID | Symbol | Alias | |
|------|----------|--------|------------------------|--|
| HGNC | 990 BCL2 | | B-cell CLL/Lymphoma 2, | |
| | 11998 | TP53 | Tumor suppressor P53, | |
| | | | | |

Η

Entity Extraction



Relation Extraction

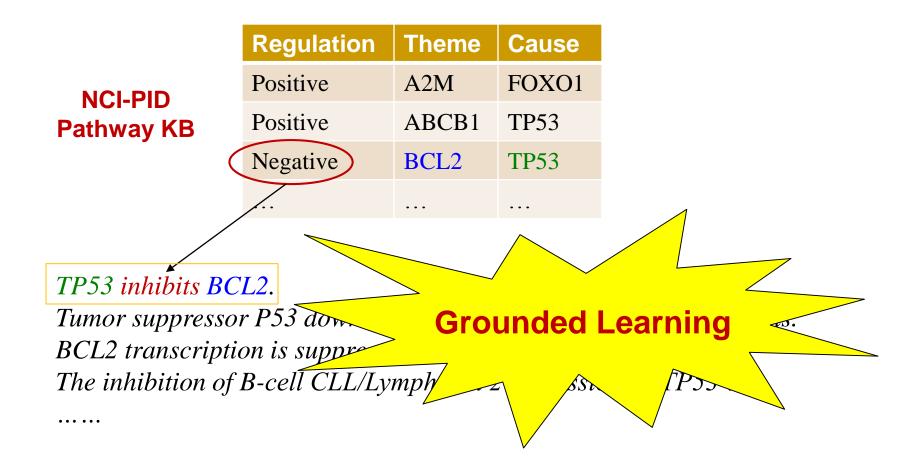
| | Regulation | Theme | Cause |
|------------|------------|-------|-------|
| NCI-PID | Positive | A2M | FOX01 |
| Pathway KB | Positive | ABCB1 | TP53 |
| - | Negative | BCL2 | TP53 |
| | | | |

TP53 inhibits BCL2.

Tumor suppressor P53 down-regulates the activity of BCL-2 proteins. BCL2 transcription is suppressed by P53 expression. The inhibition of B-cell CLL/Lymphoma 2 expression by TP53 ...

• • • • • •

Relation Extraction



Question Answering w.r.t. KB

| | Accuracy | System |
|--------------|----------|--------|
| | 84.6 | ZC07 |
| Supervised | 82.8 | FUBL |
| Unsupervised | 83.5 | GUSP |

Poon, "Grounded Unsupervised Semantic Parsing". ACL 2013.

Pathway Extraction

- Generalize distant supervision: Nested events in KB likely occur in semantic parse of some sentence
- Prior: Favor semantic parse grounded in KB
- Outperformed the majority of participants in original GENIA Event Shared Task

Parikh, Poon, Toutanova. In Progress.

Literome

| The Literome Project | | | ect | | Welcome charlie change to user id | Research | |
|----------------------|---------------------|---|-------|----------------------|--|--|----|
| filter by | ABC* | | | Gene | s: ABCA1, ABCA2, ABCA3, ABCA4, ABCA5 | (1 - 50 of 5498) | |
| genes | ZABCA1 | | ABCA1 | Abacavir | PMID: 15327972 | of abacavir (ABC; 1 -(1S,4R) | ~ |
| snps | ABCA10 | î | | | Improved antiviral activity of the aryloxymethoxyalaninyl phosphoramidate | -4-[2-amino-6-(cyclopropylamino)-9H-purin- 9-yi]-2-cyclopentene-1-methanol) | |
| diseases | ABCA12 | | | | (APA) prodrug of abacavir (ABC) is due to | (details) | |
| drugs | □ABCA13 □ABCA17P | | | | the formation of markedly increased carbovir 5'-triphosphate metabolite levels. | | |
| | ABCA2 | | | Abetalinoproteinemia | PMID: 16569910 | of ABCA1 with | -1 |

Poon *et al.*, "Literome: PubMed-Scale Genomic Knowledge Base in the Cloud", *Bioinformatics* 2014.

http://literome.azurewebsites.net

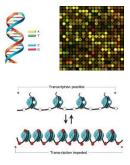
PubMed-Scale Extraction

- Preliminary pass:
 - 2 million instances
 - 13,000 genes, 870,000 unique regulations
- Applications:
 - UCSC Genome Browser, MSR Interactions Track
 - Expression profile modeling
 - Validate de novo pathway prediction
 - Etc.

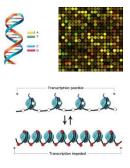
Poon, Toutanova, Quirk, "Distant Supervision for Cancer Pathway Extraction from Text". PSB 2015. *To appear*.

Evans & Rzhetsky, "Machine Science". Science, Vol. 329, 2010.

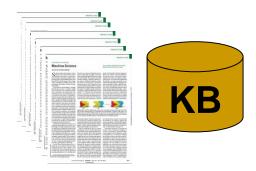


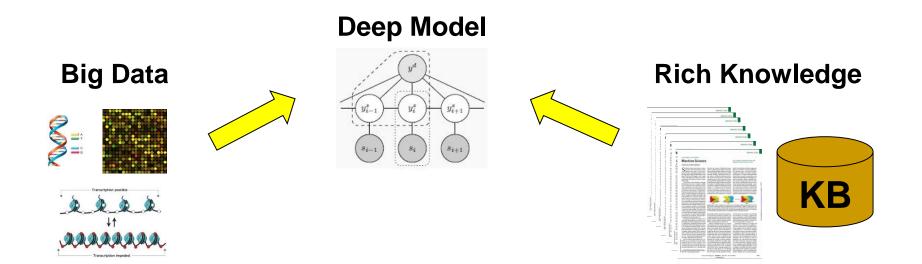


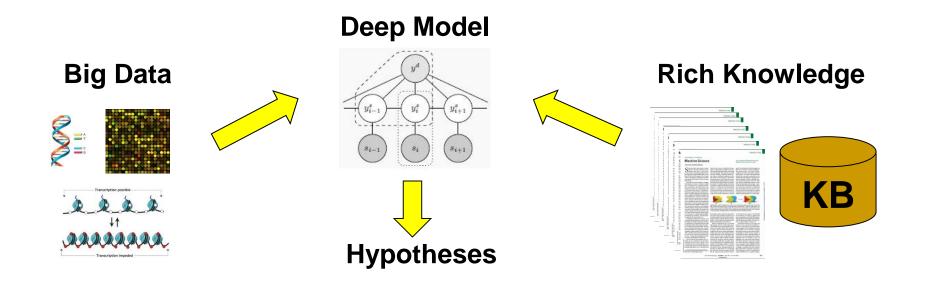


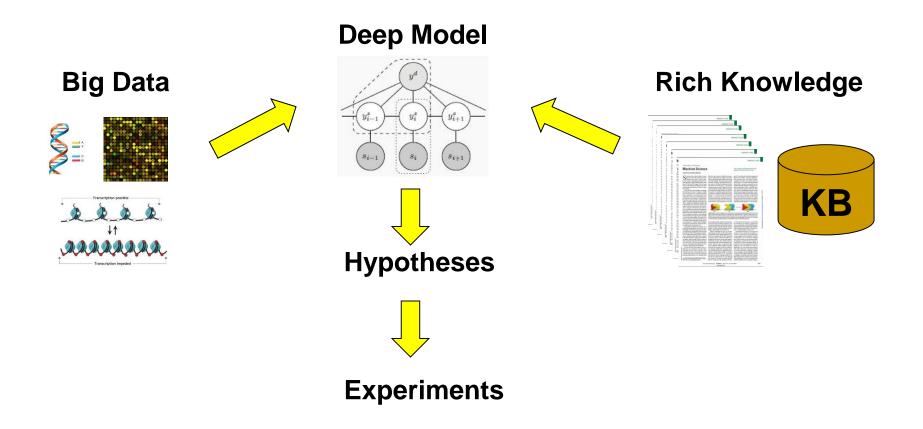


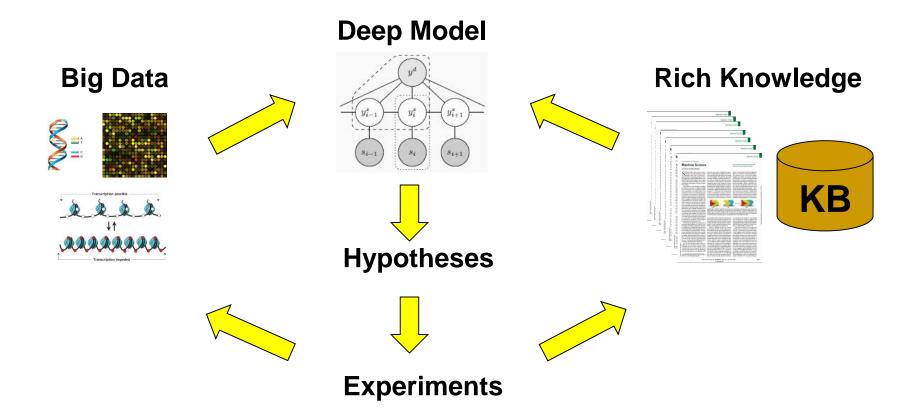
Rich Knowledge











Roadmap

• Extract richer knowledge:

- Cell type, experimental condition, ...
- Hedging, negation, ...

• Formulate coherent models:

- Supporting evidence, contradiction, ...
- Intellectual gaps, hypotheses, ...
- Integrate w. data & experiments:
 - Cancer panomics \rightarrow Driver genes / pathways
 - Single-drug response \rightarrow Drug combo prioritization





- 42-million program
 - Reading, Assembly, Explanation
 - Domain: Cancer signaling pathways
- We are in
 - PI: Andrey Rzhetsky
 - Co-PI w. James Evans, Ross King

Personalized medicine approach to treating AML

The Leukemia & Lymphoma Society (LLS) and the Knight Cancer Institute at Oregon Health & Science University are leading a pioneering collaboration to develop a personalized medicine approach to improve outcomes for patients with acute myeloid leukemia (AML), a particularly devastating cancer of the blood and bone marrow. LLS provided \$8.2 million to fund Beat AML and here is how the collaboration will work:



In coordination with the Knight Cancer Institute, Stanford University, UT Southwestern Medical Center and Huntsman Cancer Institute will collect data from 900 AML patient samples within 3 years.





Orug and biotech companies will work with the collaboration to test drug compounds that target mutations suspected of driving disease progression. Array BioPharma will be first to test a therapeutic.

Berkeley AMP Lab

OHSU





2 Illumina will perform genetic sequencing to identify mutations in the patient samples collected.



Intel will work with Knight Cancer's bioinformatics team to apply its technology to accelerate computational analysis of the mutation data collected.

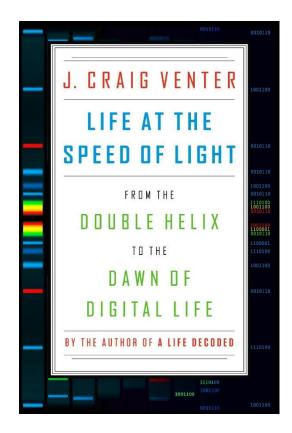
LEUKEMIA & LYMPHOMA

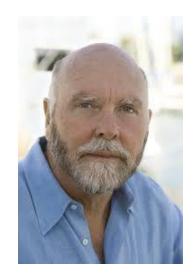
fighting blood cancers

SOCIETY



We Have Digitized Life





Next: Digitize Medicine

PERSPECTIVE

CANCER

RNAi Therapies: Drugging the Undruggable

Sherry Y. Wu,¹ Gabriel Lopez-Berestein,^{2,3} George A. Calin,^{2,3} Anil K. Sood^{1,3,4*}

RNA interference (RNAi) therapy is a rapidly emerging platform for personalized cancer treatment. Recent advances in small interfering RNA delivery and target selection provide unprecedented opportunities for clinical translation. Here, we discuss these advances and present strategies for making RNAi-based therapy a viable part of cancer management.



Knock down genes A, B, C \rightarrow Cure

Summary

- Precision medicine is the future
- Cancer systems modeling

Graphical model: Pathways + Panomics data

Extract pathways from PubMed

Machine reading by grounded semantic parsing

• Literome: KB for genomic medicine

Acknowledgments

- U. Chicago: Andrey Rzhetsky, Kevin White
- OHSU: Brian Drucker, Jeff Tyner
- Berkeley AMP Lab: David Patterson
- U. Wisconsin: Anthony Gitter
- Microsoft Research: Chris Quirk, Kristina Toutanova, David Heckerman, Ankur Parikh, Lucy Vanderwende, Bill Bolosky, Ravi Pandya

Summary

