

# Research Paper Discovery **Reimagined**

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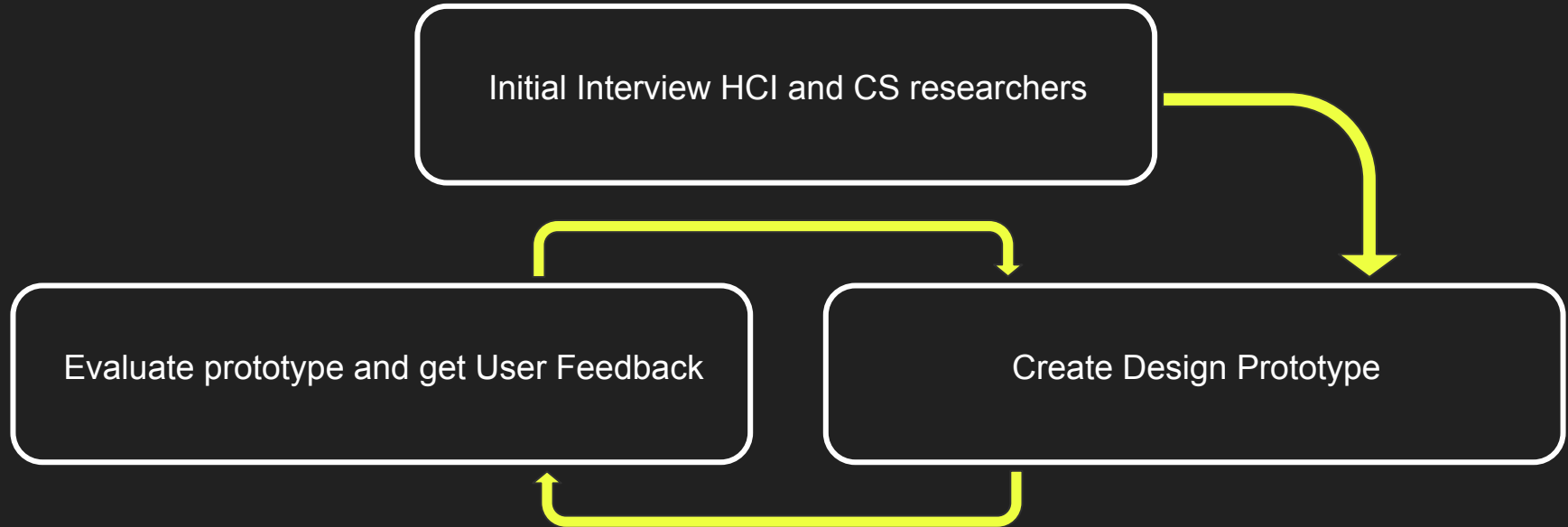
## Design Sprint

Co-creator: [Aaron Bae](#)

# The Problem

- Finding new papers requires knowing the keywords
- For a keyword search, too many irrelevant papers are returned
  - Need better way of organizing relevant papers
  - Need ways to let users easily identify which paper is relevant

# Design Process



# Initial Interview Goals

1. What are the methods that they currently use?
2. How well are they working?
3. What are the important qualities in a paper?
4. How important is “recency” of a paper?
5. What is the most challenging part in paper discovery?



# Initial Interview Results

1. Google Scholar is the most used tool
2. Other tools exist but aren't much better than Google Scholar
3. Often, conferences are a good starting point
4. Coming up with the right keywords is challenging
5. Relevance is more important than Recency
6. Knowing what colleagues are working on
7. Most time-consuming part is choosing which paper to invest more time to read
8. Simple UI is a must



# First Iteration Design Goals

- Designed as a Chrome Extension to Google Scholar

## Components:

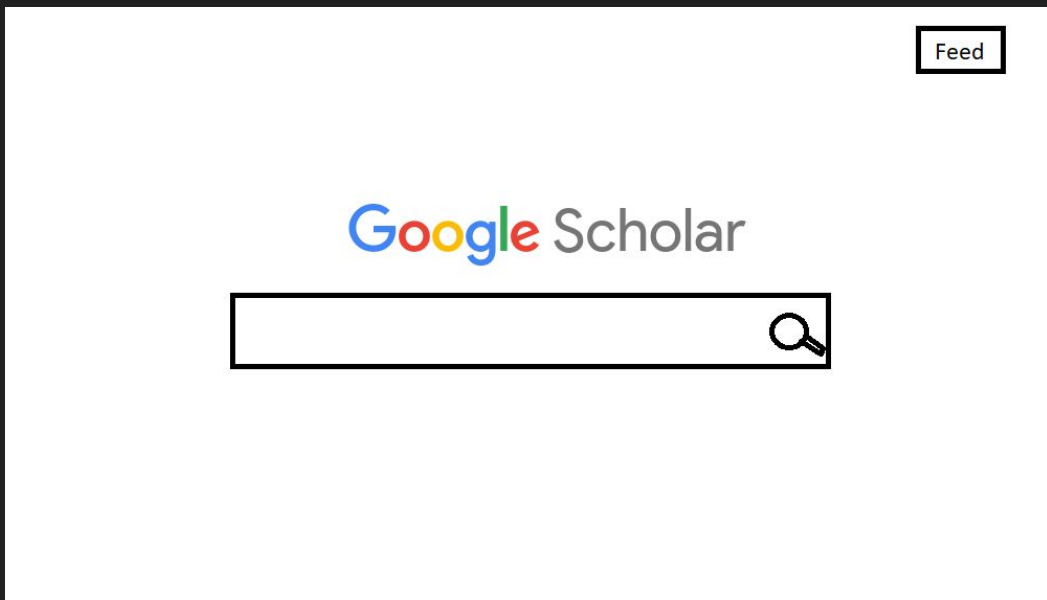
- Feed
- Paper Details
  - Key points
  - Related conferences
  - Citation tree

# Low Fidelity Prototype



Paper rankings component on the Feed Page

# Low Fidelity Prototype



Gateway button for feed feature on main Google Scholars Page.

(Intended as a Chrome Extension to Google Scholars)



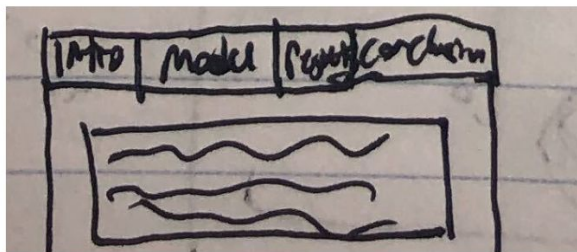
# Low Fidelity Prototype

## Paper Title: Paper title paper title

Ian Tenney, Dipanjan Das, Ellie Pavlick

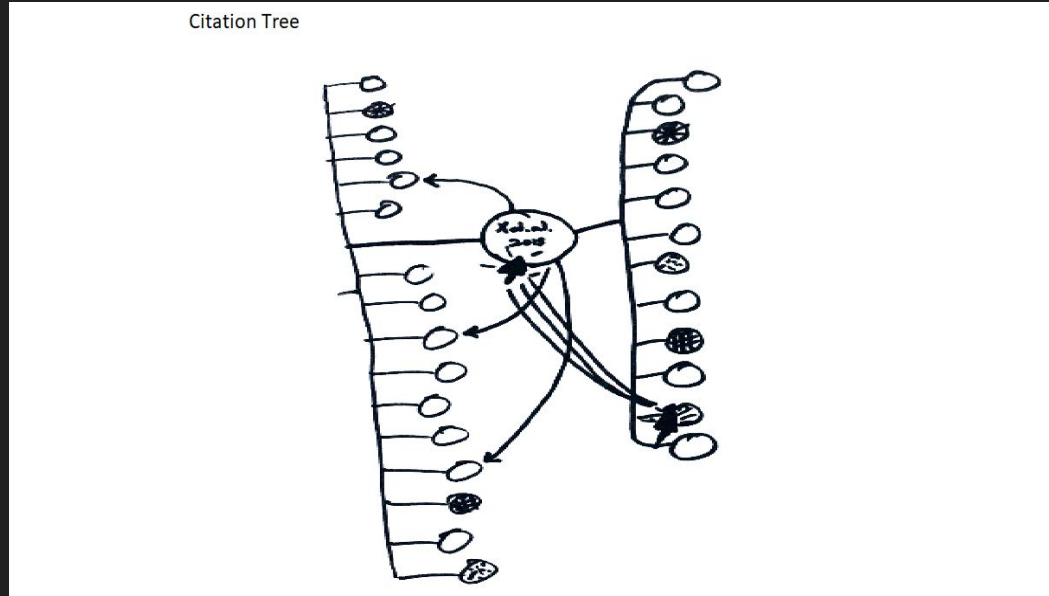
Pre-trained text encoders have rapidly advanced the state of the art on many NLP tasks. We focus on one such model, BERT, and aim to quantify where linguistic information is captured within the network. We find that the model represents the steps of the traditional NLP pipeline in an interpretable and localizable way, and that the regions responsible for each step appear in the expected sequence: POS tagging, parsing, NER, semantic roles, then coreference. Qualitative analysis reveals that the model can and often does adjust this pipeline dynamically, revising lower-level decisions on the basis of disambiguating information from higher-level representations.

### Key Points



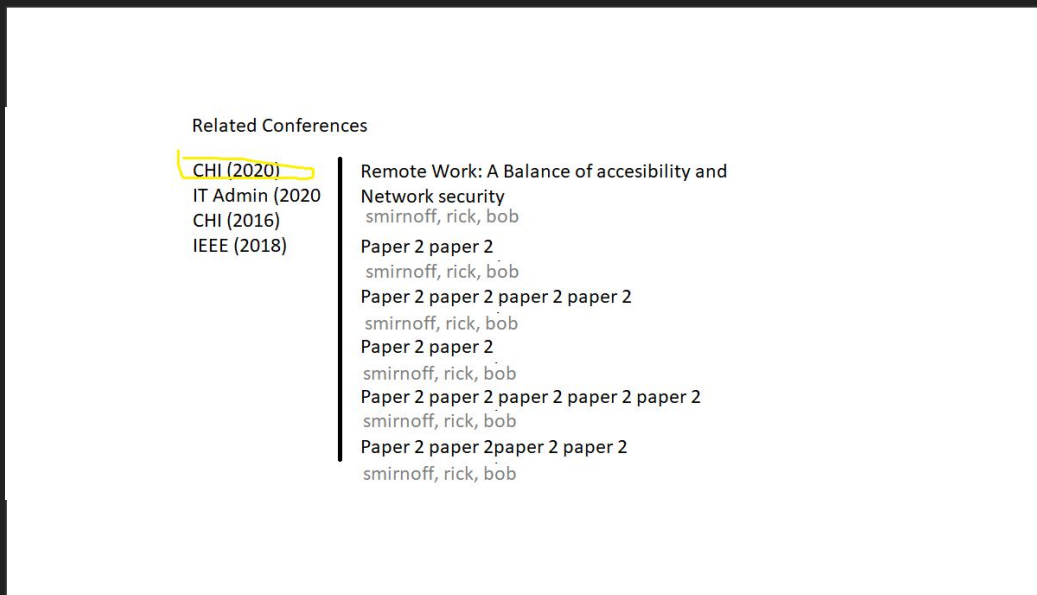
Key Points components on the Paper Details Page

# Low Fidelity Prototype



Citation tree component on the Paper Details Page

# Low Fidelity Prototype

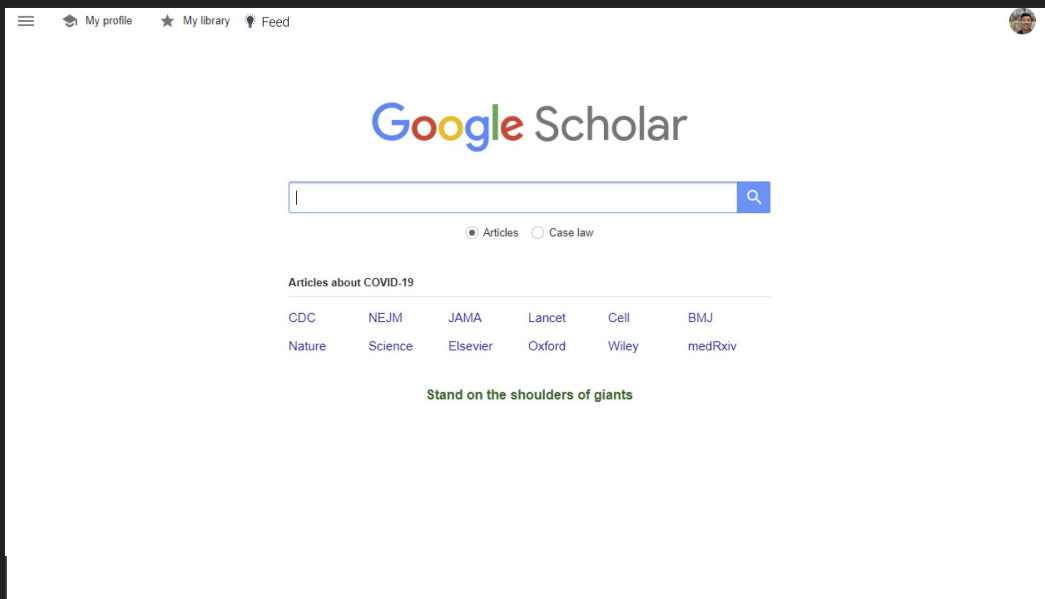


Related Conferences Component on Paper Details Page

# First Iteration Evaluation

- Presentation of our design using the low fidelity prototype
- Feedback gathered immediately after the presentation
- Feedback points:
  - Specifics of the contents on the Paper Details page would be helpful to evaluate better
  - How do you switch between different fields of studies on Feeds Page?
  - Is there a way to have more details on the authors?

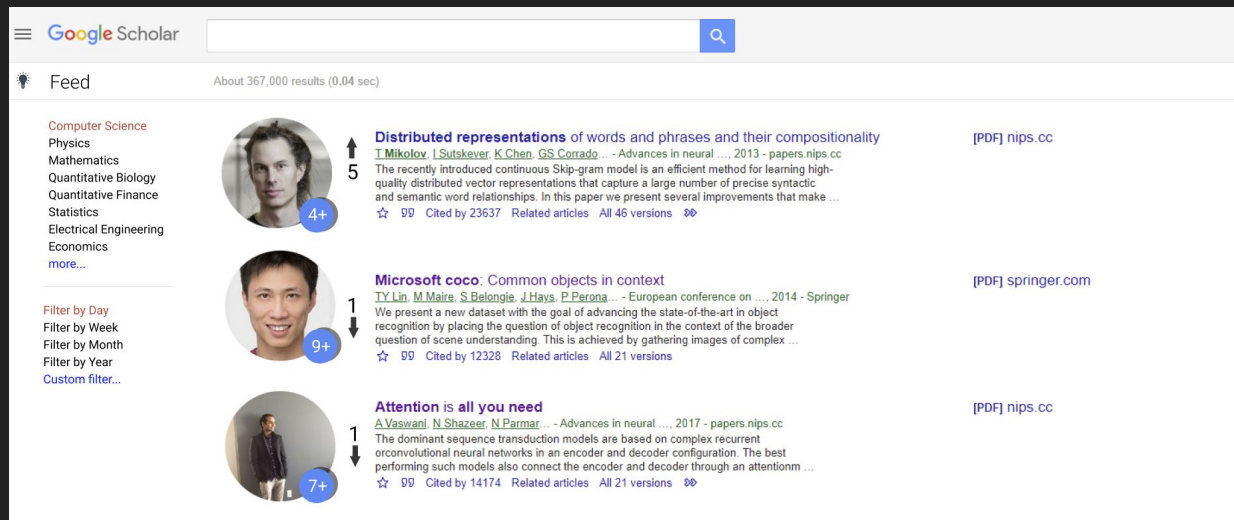
# High Fidelity Prototype



Gateway button for feed feature on main Google Scholars Page.

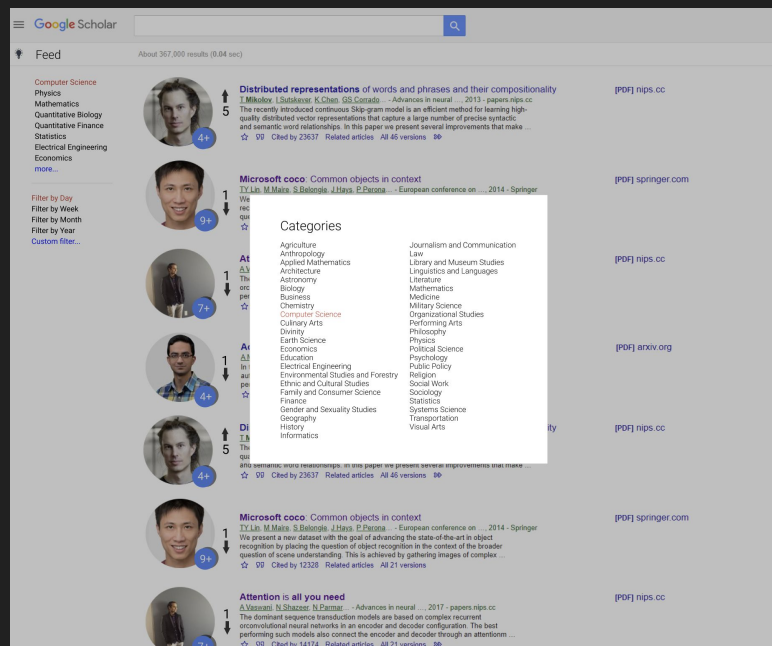
(Intended as a Chrome Extension to Google Scholars)

# High Fidelity Prototype



Paper rankings component on the Feed Page

# High Fidelity Prototype



Options to choose different Fields of Study

# High Fidelity Prototype

The image shows a Google Scholar profile for Tomas Mikolov. The profile includes a header with the name, affiliation (Santa Clara University), and a list of research interests: Artificial Intelligence, Machine Learning, Language Modeling, and Natural Language Processing. Below the header is a table of publications with columns for Title, Cited By, and Year. The table lists several papers, including 'Distributed representations of words and phrases and their compositionality', 'Efficient estimation of word representations in vector space', 'Distributed representations of sentences and documents', 'Extensions of recurrent neural network language model', 'Enriching word vectors with subword information', 'On the difficulty of training recurrent neural networks', 'Linguistic regularities in continuous space word representations', and 'Bag of tricks for efficient text classification'. A pop-up window is overlaid on the bottom right, showing details for the paper 'The dominant sequence transduction models are based on complex recurrent convolutional neural networks in an encoder and decoder configuration'. The pop-up includes a thumbnail image, the title, authors (A Vasquez, N Shazeer, N Parmar), a brief abstract, and citation information (Cited by 14174, Related articles, All 21 versions).

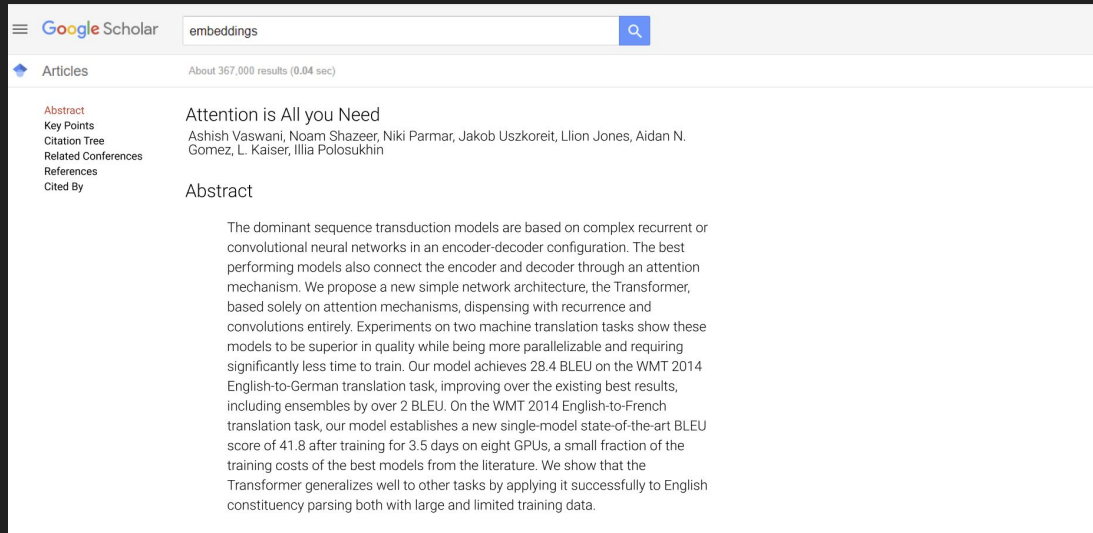
TITLE	CITED BY	YEAR
<a href="#">Distributed representations of words and phrases and their compositionality</a> T Mikolov, I Sutskever, K Chen, GS Corrado, J Dean Neural information processing systems	23774	2013
<a href="#">Efficient estimation of word representations in vector space</a> T Mikolov, K Chen, G Corrado, J Dean arXiv preprint arXiv:1301.3781	18886	2013
<a href="#">Distributed representations of sentences and documents</a> Q Le, T Mikolov International conference on machine learning, 1188-1196	6722	2014
<a href="#">Extensions of recurrent neural network language model</a> T Mikolov, S Kombrink, L Burget, J Cernocký, S Khudanpur 2013 IEEE international conference on acoustics, speech and signal ...	5159	2011
<a href="#">Enriching word vectors with subword information</a> P Bojanowski, E Grave, A Joulin, T Mikolov Transactions of the Association for Computational Linguistics 5, 135-146	4637	2017
<a href="#">On the difficulty of training recurrent neural networks</a> R Pascanu, T Mikolov, Y Bengio International conference on machine learning, 1310-1318	3479	2013
<a href="#">Linguistic regularities in continuous space word representations</a> T Mikolov, W Yin, G Zweig Proceedings of the 2013 conference of the north american chapter of the ...	3192	2013
<a href="#">Bag of tricks for efficient text classification</a> A Joulin, E Grave, P Bojanowski, T Mikolov arXiv preprint arXiv:1607.01759	2376	2016

[The dominant sequence transduction models are based on complex recurrent convolutional neural networks in an encoder and decoder configuration](#)  
The best performing such models also connect the encoder and decoder through an attention ...  
Cited by 14174 Related articles All 21 versions

## Author Details Pop Up



# High Fidelity Prototype



Paper Title, Authors, and Abstract components on Paper Details Page

# High Fidelity Prototype

## Key Points

### **Introduction**

Background

Model Architecture

Why Self-Attention

Training

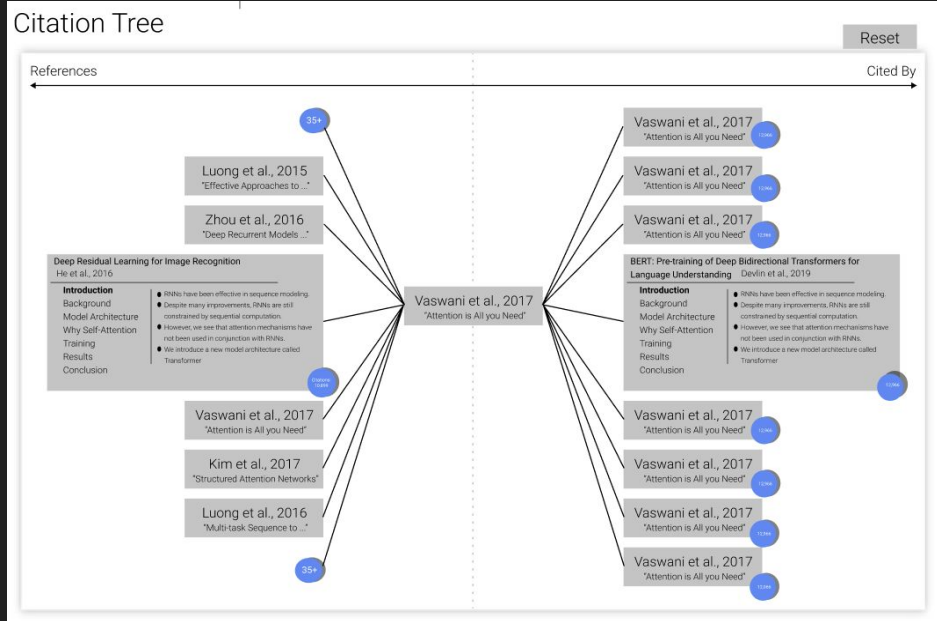
Results

Conclusion

- RNNs have been effective in sequence modeling.
- Despite many improvements, RNNs are still constrained by sequential computation.
- However, we see that attention mechanisms have not been used in conjunction with RNNs.
- We introduce a new model architecture called Transformer

Key Points component on the Paper Details Page

# High Fidelity Prototype



Citation Tree on the Paper Details Page

# High Fidelity Prototype

## References

Sequence to Sequence Learning with Neural Networks  
Ilya Sutskever, Oriol Vinyals, Quoc V. Le 2014

Effective Approaches to Attention-based Neural Machine Translation  
Thang Luong, Hieu Pham, Christopher D. Manning 2015

Deep Recurrent Models with Fast-Forward Connections for Neural Machine Translation  
Jie Zhou, Y. Cao, X. Wang, Peng Li, W. Xu 2016

Neural Machine Translation in Linear Time  
Nal Kalchbrenner, Lasse Espeholt, K. Simonyan, A. Oord, A. Graves, K. Kavukcuoglu 2016

A Deep Reinforced Model for Abstractive Summarization  
Romain Paulus, Caiming Xiong, R. Socher 2018

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1 2 3 4 5 6 7 8 9 10 [Next](#)

References Component on the Paper Details Page

# Second Iteration Evaluation

- Cognitive walkthrough and post-exercise questions via Virtual Interview
- Tasks that Participants attempted:
  1. Find the list of Computer Science papers that are trending on feed
  2. Find the list of Informatics papers that are trending on feed
  3. Find the key points from “Attention is all you need” paper from Feeds list
  4. Find a paper that is cited by “Attention is all you need” paper

# Second Iteration Evaluation

- Cognitive walkthrough and post-exercise questions via Virtual Interview
- Post-Exercises Questions:
  1. What is your overall impression?
  2. How many of the 4 tasks above could you complete?
  3. Were there any aspects of the prototype that made it difficult to complete the tasks?
  4. If this prototype were to be implemented as a Chrome Extension, would you download and use it?
  5. Would you find an application like this helpful?
  6. Would you use it on a regular basis?

# Second Iteration Evaluation

- Cognitive walkthrough and post-exercise questions via Virtual Interview
- Main Feedback Points:
  1. All 4 tasks were easily completed by all interviewees
  2. Google Extension idea is well received
  3. Features overlap with other websites, but having them on Google Scholar's page is an advantage
  4. Difficult to gauge the usefulness of Key Points, because it will depend on the content
  5. Overall, participants are very impressed, and willing to try it out once developed

# Link to our Figma Prototype

<https://www.figma.com/proto/lqUszliOzubDax5me1SP79/INF231-Prototype?node-id=39%3A56&scaling=scale-down>



Thank You