EECS 764 – ANALYSIS OF ALGORITHMS FINAL PROJECT

ANALYSIS OF ALGORITHMS IN SOCIAL NETWORKING SITES.

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Why was this topic chosen?

Considering the Union of the sets of user-base of all the social networking platforms, there are 3.8 Billion people who are affected by the algorithms used here.

From Marriages to Elections, Celebration to Depression, these platforms play a role in every thing. Facebook, Twitter, Snap-Chat and LinkedIn are some of the fastest growing and most invested web applications today. Your actions can get you hired as well as fired.

However, the success and growth of these platforms depend upon how relevant are the articles and posts to a user. Social Network is one of the rarest domains where relevancy is more important than speed. A good example of failure was Orkut. Inability to understand what is relevant to a user and showing posts which were not interesting to the active user made it a boring web application and ultimately led too it's fall. This "relevancy" is hugely dependent on the algorithms in the backend.

WHAT IS RELEVANCY?

As a definition it is very simple. It simply means showing relevant posts and suggestions to a user. However, in terms of business, relevancy is everything. Majority of the algorithms which are being used in Facebook and other social networking sites focus on showing relevant articles, posts, friend suggestions and……the advertisements.

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SO, THIS PROJECT FOCUSES ON TWO REAL LIFE APPLICATIONS:
THE NEWSFEED AND FRIEND SUGGESTIONS

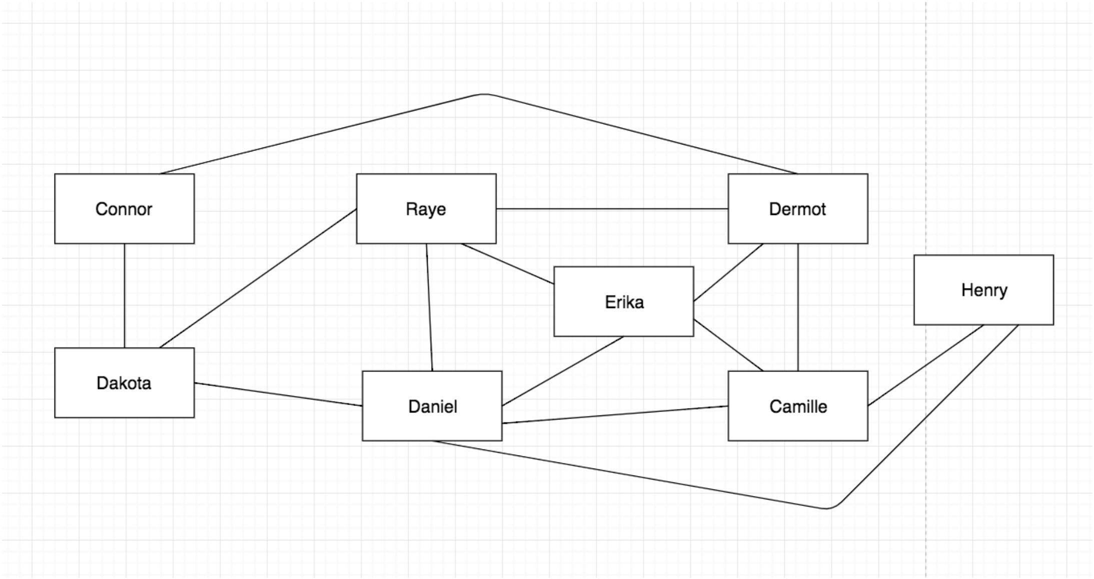
GRAPH ALGORITHMS

The concepts of graphs, edges, nodes and weights can be said to be the major constituents of the backbone of social network.

Apart from Facebook, most of the social networking sites like LinkedIn are built upon graphs. Let's go deeper to understand their working with a few diagrams in the next few slides.

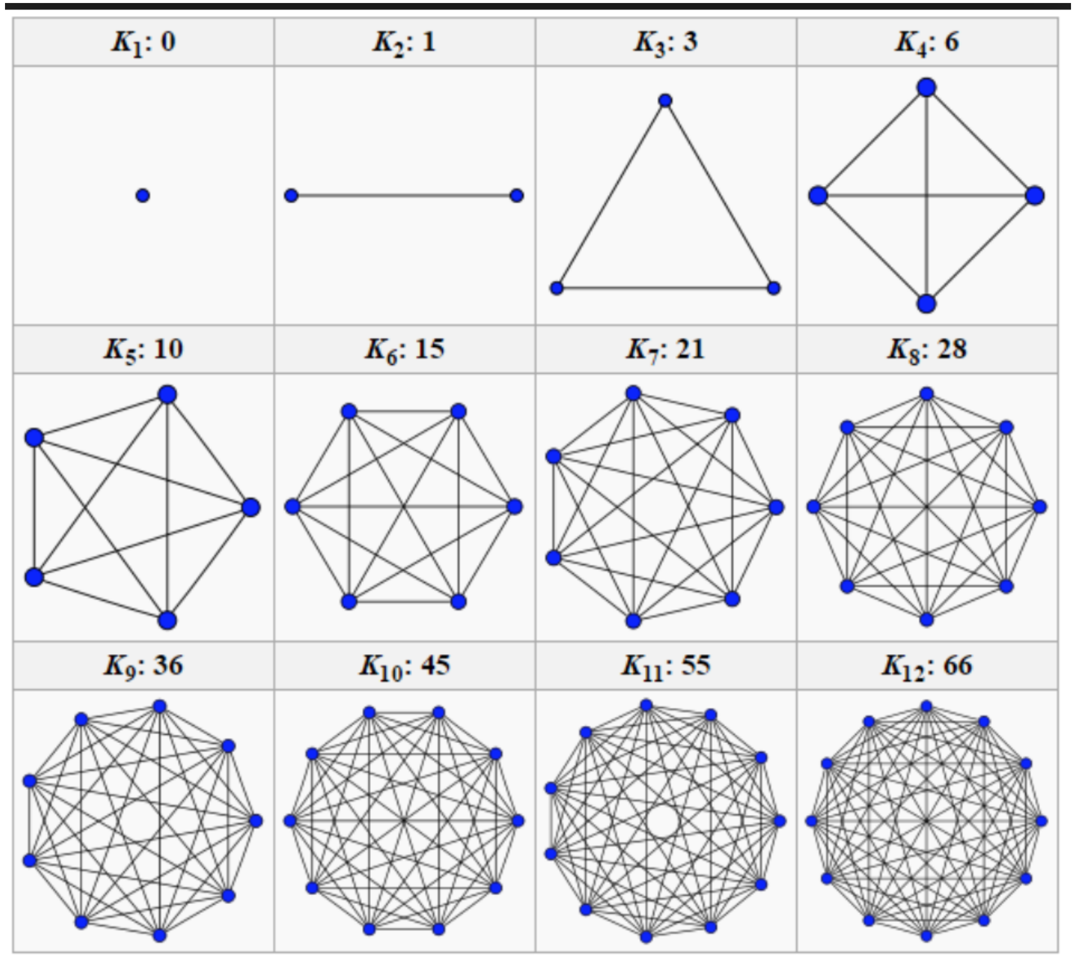
SOCIAL NETWORK-GRAPHS ARCHITECTURE

Let's understand how social networks are represented as graphs. Each of the nodes shown here represent the users (with name) and the edges represent the connections. (Note: This analysis is not valid for Facebook)



It is quite simple till this point because we have only 8 friends in your network till now.

SOCIAL NETWORK-GRAPHS ARCHITECTURE



Okay now let's get realistic. Generally the network of friends (Facebook), followers (Instagram) or connections (LinkedIn) increase rapidly. The growth does become stagnant but that actually comes at a very later stage. Till then your simple network which was shown in the last slide becomes something the K12 graph with 12 vertices.

As the graph, or let's say your network grows denser and denser, it becomes impossible for the app to show "every content from everybody". For Facebook, the average selection rate of **posts** and **friend suggestions** that make up to your news feed is just 2%. Rest of the 98% posts and friend suggestions are rejected.

So now comes the major question that arises is, when the graph or the network has grown dense, on what basis does the app choose to show you the " most relevant" posts and suggestions on your newsfeed?

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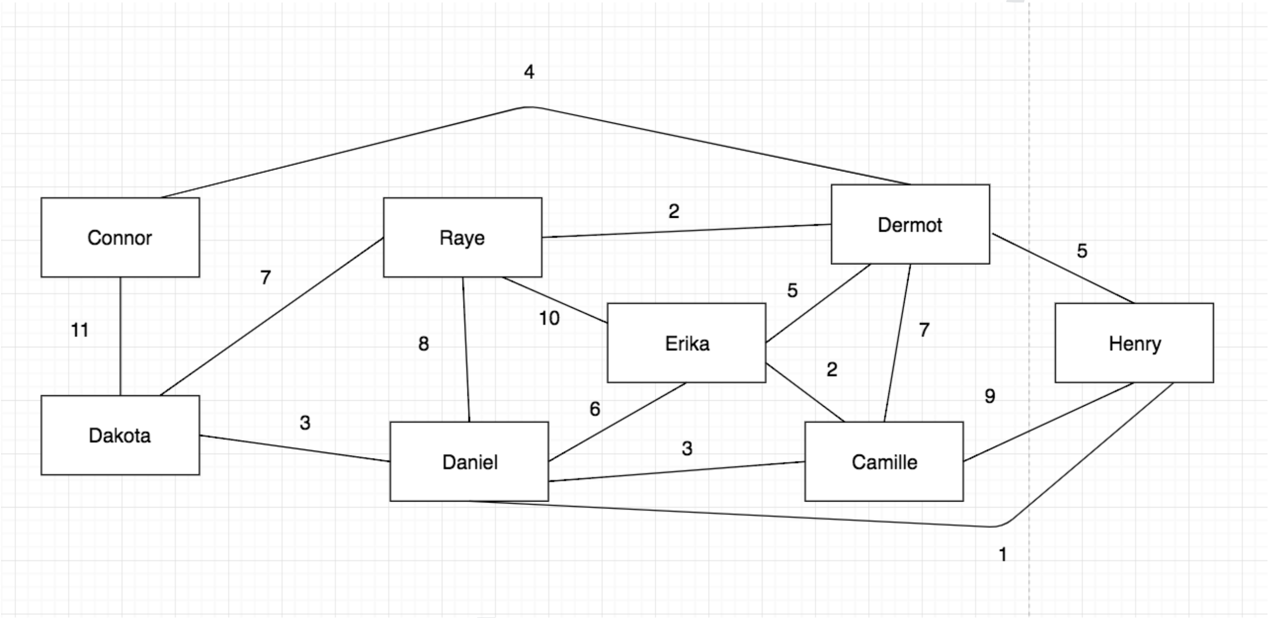
GENERAL WEIGHING BASED ON INTERACTIONS

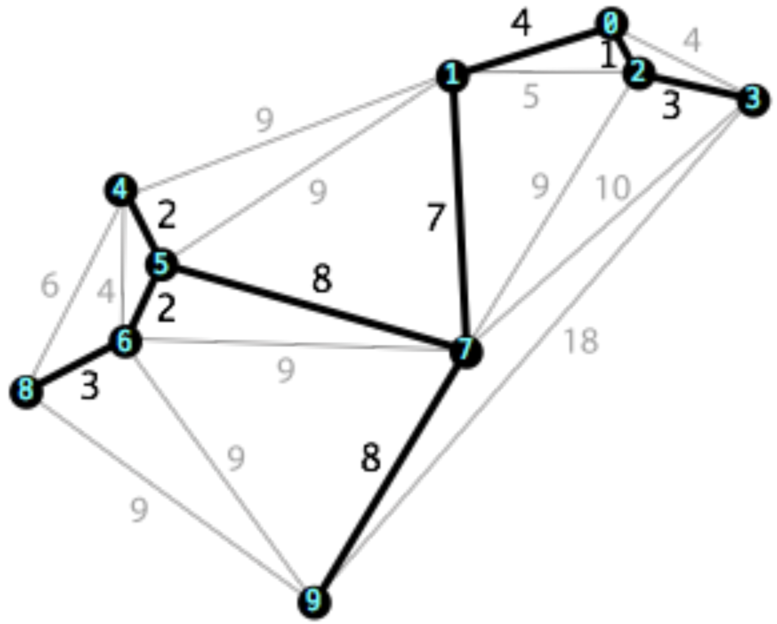
The general weighing method was used in the early days of social networking, that is between 2007 and 2010. It was indeed simple with one simple logic:

"Now the edges are numbered by weights. So what exactly is the basis for these weights? It's the interaction. *More interaction in terms of likes, comments, tags and share **decrease** the weight.*"

The logic was to apply greedy algorithms and get a Minimum Spanning Tree. Two friends who rarely interact with each other will have a heavy edge (connection) between them.. Eventually with increasing weight, the chances of making it into the MST decreases.



SOCIAL NETWORK-GREEDY APPROACH



Whom do you see in your friend suggestion? Is he or she from your department, from your school, from your office or from your classroom?

Who comes up in your friend suggestion is decided by the greedy approach. The greedy algorithms which are used here create a Minimum Spanning Tree, in simple words, the most relevant, most interacted, most interesting set of edges. Note: This is not what Facebook follows today but once upon a time, nearly a decade ago, every social networking site followed the Minimum Spanning Tree Approach to decide what should come up in your feed and who should show up in your friend suggestion.

The commonly used algorithms for MST are Kruskal's, Prim's and Dijkstra's algorithms. In this project we will analyze the first two as there is a minor advantage of one over the other when the connection network becomes very dense.

KRUSKAL'S ALGORITHM

- MAKE-SET(v) puts v in a set by itself
- FIND-SET(v) returns the name of v's set
- UNION(u, v) combines the sets that u and v are in

MST-Kruskal(G, w)

$A \leftarrow \emptyset$
for each vertex $v \in V[G]$
    do MAKE-SET(v)
sort the edges of E into nondecreasing order by weight w
for each edge $(u, v) \in E$, taken in nondecreasing order by weight
    do if FIND-SET$(u) \neq$ FIND-SET(v)
        then $A \leftarrow A \cup \{(u, v)\}$
            UNION(u, v)
return A

Working procedure :

- Sort edges by weight/cost.
- At each iteration we select the edge with the lowest weight. (This weight is assigned by quantifying the interaction between two users)
- The next lightest/cheapest edge is selected, keeping the constraint in mind that no cycles should be formed.
- The chosen edges are added using union..
- Selected edges can be totally disjoint.
- Edges which form cycle are not allowed.

Time Complexity :

In Kruskal's algorithm, most time consuming operation is sorting because the total complexity of the Disjoint-Set operations will be **O(ELogV),** which is the overall Time Complexity of the algorithm.

PRIM'S ALGORITHM

```
MST-PRIM(G, w, r)
for each u ∈ G.V
    u.key = ∞
    u.π = NIL
r.key = 0
Q = G.V
while Q ≠ Ø
    u = EXTRACT-MIN(Q)
    for each v ∈ G.Adj[u]
        if v ∈ Q and w(u, v) < v.key
            v.π = u
            v.key = w(u, v)
```

Working procedure :

- Maintain two disjoint sets of vertices. One containing vertices that are in the growing spanning tree and other that are not in the growing spanning tree.
- Select the cheapest vertex that is connected to the growing spanning tree and is not in the growing spanning tree and add it into the growing spanning tree. This can be done using Priority Queues. Insert the vertices, that are connected to growing spanning tree, into the Priority Queue.
- Check for cycles. To do that, mark the nodes which have been already selected and insert only those nodes in the Priority Queue that are not marked.

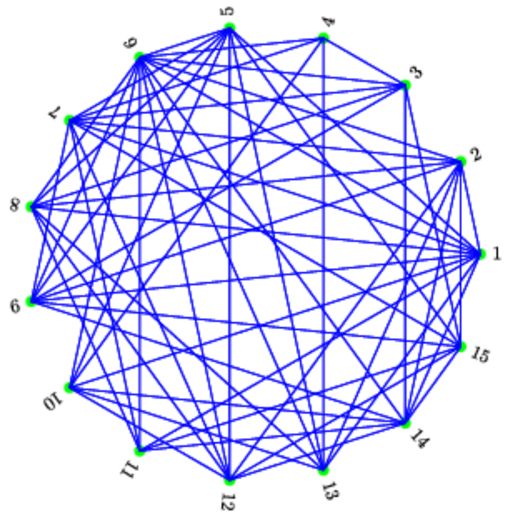
Time Complexity : The time complexity of the Prim's Algorithm is **O((V+E)LogV)** because each vertex is inserted in the priority queue only once and insertion in priority queue take logarithmic time.

DENSE NETWORK (DENSE GRAPH)

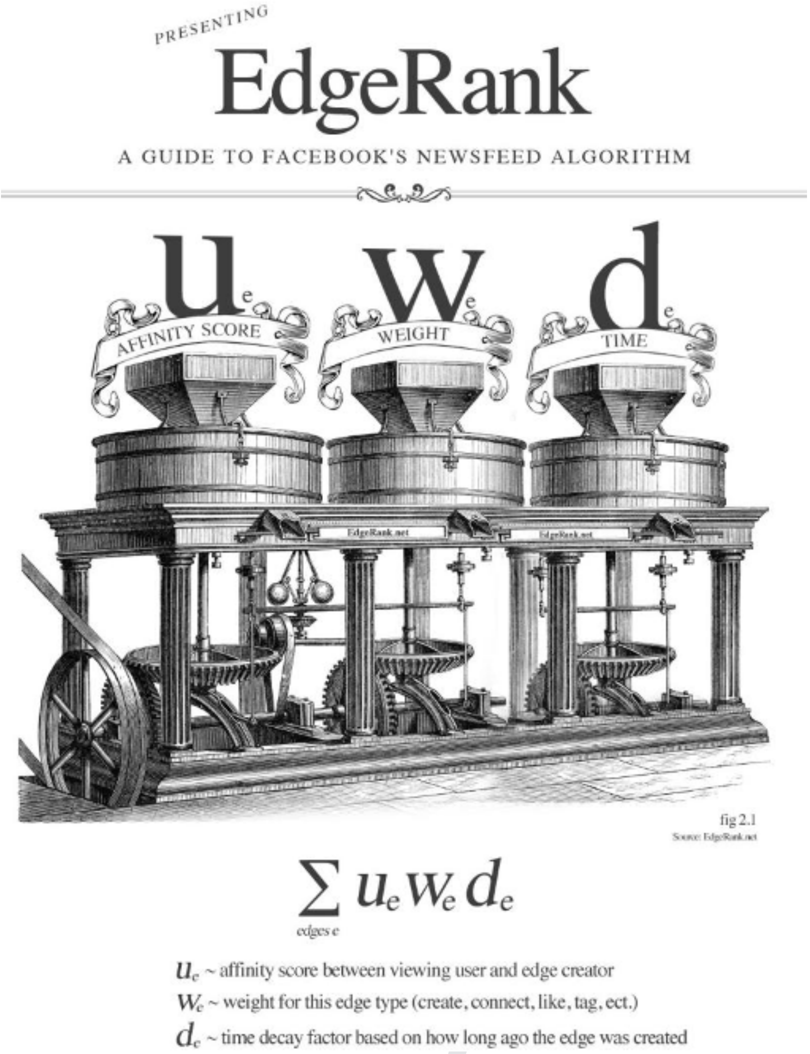
WHICH ONE IS PREFERRED, PRIM'S OR KRUSKAL'S?

Although Prim's algorithm's complexity can be further improved with a Fibonacci Heap. However, in a Sparse network, no significant difference has been noted between the two algorithms.

However, it has been noticed that when the social network gets very Dense, Prim's works better as it does not allow any disjoint sets and the tree is always connected and grows from vertex to vertex.



EDGERANK ALGORITHM



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EDGERANK ALGORITHM: QUANTITY & QUALITY

Story of Development: Facebook’s EdgeRank algorithm looks very simple. However, it proved to be a game changer for Facebook against its competitors. Newsfeed content plays a major role in the survival of a social networking site. If the content that is coming to my newsfeed is not interesting, I would rarely open the site. When Facebook realized that its competitors were being equally good in showing interesting and relevant contents, it decided to devise an algorithm which would be more precise in deciding the contents for newsfeed and friend suggestion. They came up with Edgerank algorithm which not only adds weights to the edges based on the interaction but also takes into consideration the “**type of interaction**”. Since this is a commercial algorithm, Facebook disclosed only 3 components of Edgerank. Rest of the components that this algorithm takes into consideration and propriety to Facebook Inc. and are not available in public.

In Stage I, EdgeRank weighs the edges of the graph. The way it weighs the edges is mysterious and cannot be anticipated at all. Did Facebook bring a complete overhaul? No, not until 2016. Till then Facebook used EdgeRank which was nothing but an unknown way of weighing the graphs.

In Stage II, it still used a greedy approach to form a Minimum Spanning Tree. However, since the edges were weighed differently, the Minimum Spanning Tree that is formed is also very different.

EDGERANK ALGORITHM: QUANTITY & QUALITY

Some anticipatory research has been done to figure out the undisclosed parameters with which EdgeRank Algorithm has non-randomized the assignment of posts and visibility. Here is a paper which throws some light based on trials and anticipation, however, no concrete evidence has been found to figure out the exact parameters and their weightage in edges.

The World of Edgerank: Rhetorical Justifications of Facebook's News Feed Algorithm

Computational Culture (5), Special Issue on Rhetoric and Computation

24 Pages • Posted: 15 Apr 2016

Andreas Birkbak
Aalborg University Copenhagen

Hjalmar Carlsen
University of Copenhagen - Department of Sociology

Date Written: January 15, 2016

QUANTITY & QUALITY: NON-RANDOMISED ASSIGNMENT OF POSTS.

Known Parameters of EdgeRank:

- U: How much is the interaction in terms of quantity?
- W: What type (quality) of interaction is taking place? The concept that various actions like comments, likes, tagging and sharing weigh differently and could represent different intensity of friendship was introduced for the first time.
- D: Decay is the time that has passed after the content was posted on the wall. Latest posts would be ranked higher and will have more chances to make a way into your newsfeed.

Formula and factors [edit]

In 2010, a simplified version of the EdgeRank algorithm was presented as:

$$\sum_{\text{edges } e} u_e w_e d_e$$

where:

u_e is user affinity.

w_e is how the content is weighted.

d_e is a time-based decay parameter.

- User Affinity: The User Affinity part of the algorithm in Facebook's EdgeRank looks at the relationship and proximity of the user and the content (post/status update).[1]
- Content Weight: What action was taken by the user on the content.[1]
- Time-Based Decay Parameter: New or old. Newer posts tend to hold a higher place than older posts.[1]

Some of the methods that Facebook uses to adjust the parameters are proprietary and not available to the public.[2]

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EDGERANK - BUSINESS

- **Two Step Process**:
  - EdgeRank uses the parameters U, W and D (as described in previous slide) and also some other parameters which are unknown to the public, to assign weights to edges.
  - Once the weight has been assigned, greedy algorithms are used to form the sub graph (Minimum Spanning Tree). The newsfeed is populated based on the newly formed network from the Minimum Spanning Tree.
- **A Business Strategy:**
  - EdgeRank was not an algorithm to have better control on newsfeed than the rivals could have, it was also a tool for Facebook to have manipulative power on the graph formation and thereby have some kind of control over who sees what.
  - EdgeRank gave birth to paid content and Social Media Marketing in 2010
  - With EdgeRank, Facebook was able to introduce Fan Pages and Business Pages

EDGERANK - BUSINESS

Various business schools have done extensive research and later on case studies on EdgeRank.
Here is one of the resources.

The Effect of Advertising Content on Consumer Engagement: Evidence from Facebook*

Dokyun Lee
The Wharton School

Kartik Hosanagar
The Wharton School

Harikesh S. Nair
Stanford GSB

Abstract

We investigate the effect of social media content on customer engagement using a large-scale field study on Facebook. We content-code more than 100,000 unique messages across 800 companies engaging with users on Facebook using a combination of Amazon Mechanical Turk and state-of-the-art Natural Language Processing algorithms. We use this large-scale database of advertising attributes to test the effect of ad content on subsequent user engagement – defined as *Likes* and comments – with the messages. We develop methods to account for potential selection biases that arise from Facebook's filtering algorithm, EdgeRank, that assigns posts non-randomly to users. We find that inclusion of persuasive content – like emotional and philanthropic content – *increases* engagement with a message. We find that informative content – like mentions of prices, availability and product features – *reduce* engagement

EDGERANK - COMPLEXITY

- EdgeRank was still based on Graphs and MST approach till 2013.
- Like the other greedy algorithms, Edge Rank also had iteration (sort/prioritize) and recursive (find and union) approach.
- The algorithm had the same O(nLogn) complexity.
- Only the way of weighing edges changed, not the
- Facebook was now able to create a very optimized MST which was very-very different from anyone who wished to compete with them.

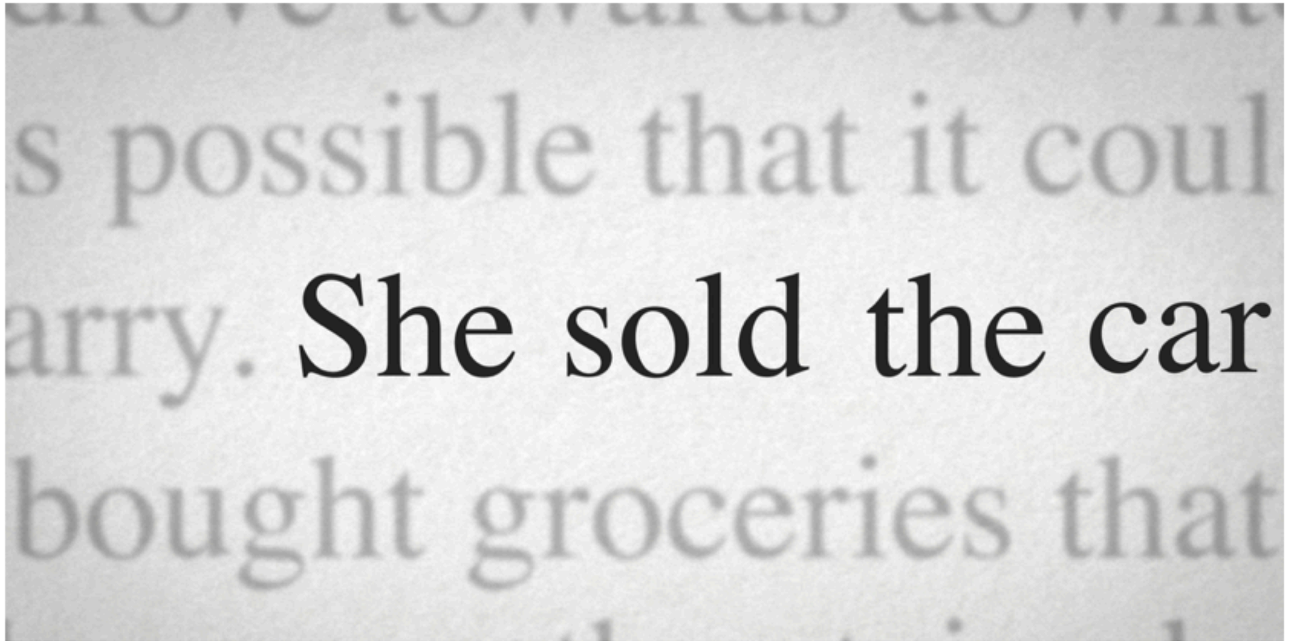
DEEPTEXT ALGORITHM

facebook Engineering

Open Source ⌄ Platforms ⌄ Infrastructure Systems ⌄ Physical Infrastructure ⌄ Video Engineering & AR/V

POSTED ON JUN 1, 2016 TO AI RESEARCH, CORE DATA, ML APPLICATIONS

Introducing DeepText: Facebook's text understanding engine



In 2016, Facebook came up with **DeepText**, a Convolutiona Neural Networks based Text Understanding Engine with near-human accuracy

DEEPTEXT ALGORITHM- YANN LECUNN

Very Deep Convolutional Networks for Text Classification

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Character-level Convolutional Networks for Text Classification*

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VERY DEEP MULTILINGUAL CONVOLUTIONAL NEURAL NETWORKS FOR LVCSR

Tom Sercu[1,2] *Christian Puhrsch*[1] *Brian Kingsbury*[2] *Yann LeCun*[1]

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[2] IBM T. J. Watson Research Center, Yorktown Heights, NY, 10598, U.S.A.

YANN LECUNN

- He is the pioneer of Convolutional Neural Networks.
- Often called the father of CNN, he pioneerd CNN in his 1988 paper on recognizing zipcodes and segmenting mails.
- He joined Facebook in 2013 as the Director of Facebook AI Research Group and currently serving as the VP of Facebook.
- Success and existence of DeepText and various speech and text understanding conversation AI algorithms are attributed to him.

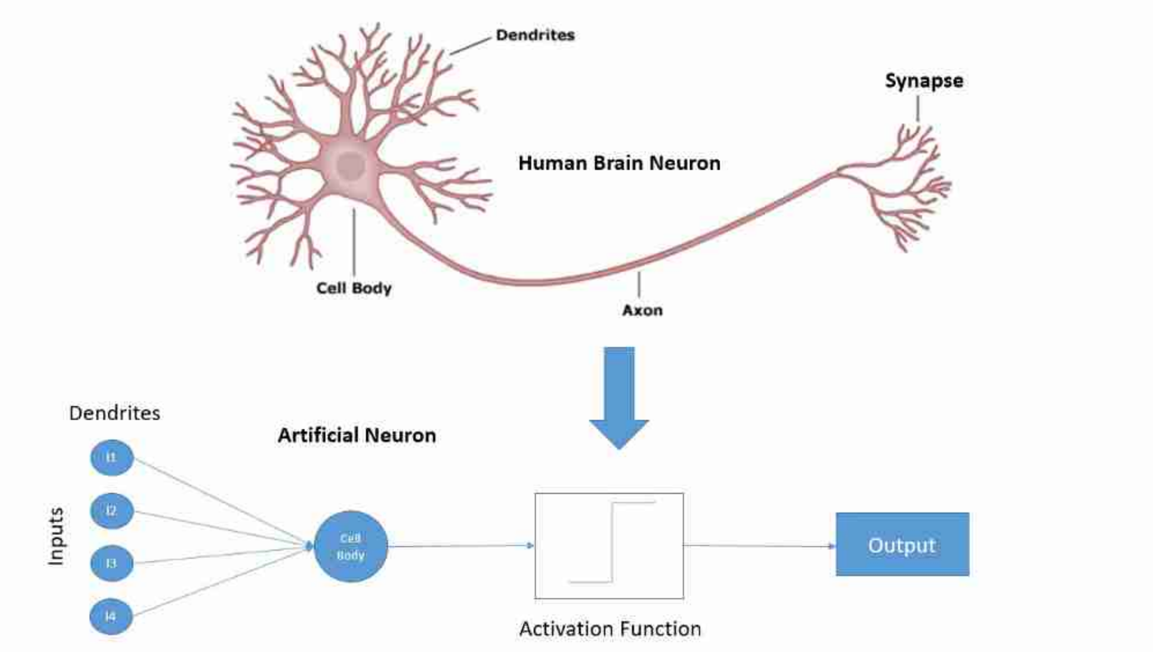
DEEPTEXT ALGORITHM- COMPLEXITY ANALYSIS

In 2016, under the leadership of Yann Lecunn, Facebook introduced and implemented the DEEPTEXT Algorithm for enhancing their capabilities of assigning posts and friend suggestions on newsfeed of there users.

DeepText is built upon convolutional neural network and thus, known to have heavy computational burden. Run-Time is O(n^4+n^2)<=>O(n^4)

Where n represents neuron. Each neuron from each layer of the CNN (Refer to Slide: 27-29)

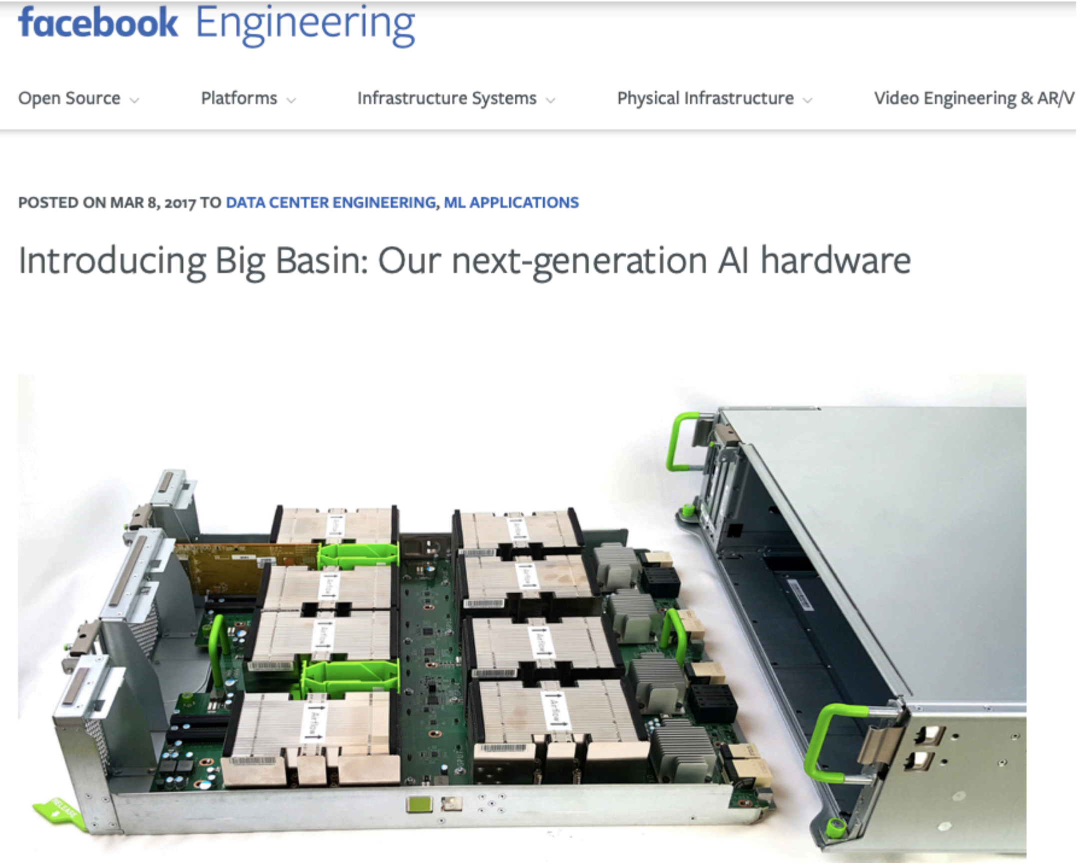
DeepText is often confused as just another Natural Language Processing Model used in Siri or Alexa. However, DeepText's language understanding capabilities are way more advanced than traditional NLP model. We will see more details in the upcoming slides.



DEEPTEXT ALGORITHM- ANALYSIS

Convolutional Neural Networks come with very heavy computational burden (in the order of O(n^4)). On top of that, Facebook as Billions of users generating Terabytes of data per day. So, how does Facebook use DeepText and yet show no signs of time lag?

Even with heavy burden, DeepText Algorithm can understand with near-human accuracy the textual content of several thousands posts per second, spanning more than 20 languages, thanks to the dedicated server of Facebook for Artificial Intelligence, called Big Basin Server.



DEEPTEXT ALGORITHM- CONTEXTUAL UNDERSTANDING

Text Understanding: Simply saying, just like we humans understand the meaning of the text we are reading, machines can do the same. What they cannot do is understand ‘accurately’ and understand ‘contextually’. While the accuracy has been resolved with more and more quality data sets being available for training.

While most companies like Apple and Amazon are working on NLP, Facebook played the masterstroke by hiring Yann LeCunn and then developing a text understanding algorithm using CNN.

Although these two NLP based text understanding models and CNN based text understanding models are often considered to be equal in terms of text understanding, they are very much apart when it comes to contextual understanding.

"Is he hungry?" & "He is hungry" have a different context. DeepText understands this contextual difference.

DEEPTEXT ALGORITHM- CONTEXTUAL UNDERSTANDING

NLP has various algorithms like TFIDF and Bag of Words which work by tokenizing the words in a sentence. That is each word is given an integer marking and the frequency of those integers are taken into account to create an understanding of the text sentence.

For example, NLP will treat “Brother” and “Bro” differently.

However, the DeepText was developed to have “contextual” understanding. Statistically speaking, the order of the words is also taken into consideration before arriving at a conclusion about the meaning of the text. That is Facebook has written on the Facebook Engineering page “near human” accuracy.

For example, “He is Hungry” and “Is he Hungry?” are two sentences with same words and same frequency. However, the contextual meaning is quite different.

Reference: https://engineering.fb.com/core-data/introducing-deeptext-facebook-s-text-understanding-engine/

Deeper understanding

In traditional NLP approaches, words are converted into a format that a computer algorithm can learn. The word “brother” might be assigned an integer ID such as 4598, while the word “bro” becomes another integer, like 986665. This representation requires each word to be seen with exact spellings in the training data to be understood.

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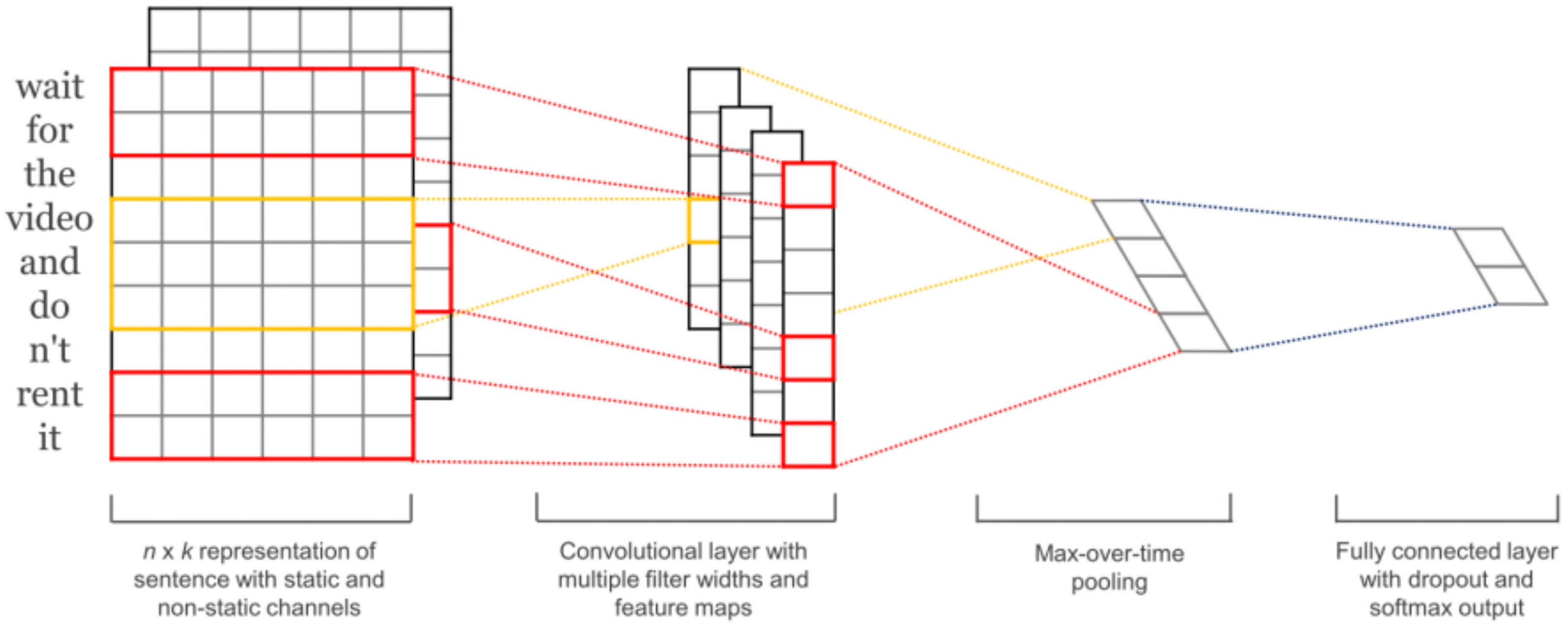
DEEPTEXT ALGORITHM- CNN LAYERS

INPUT LAYER

Input Layer: IPL does not take a word but a set of words. The keyword and a few more words before and after the keyword are also taken to get the context.

CONVOLUTION LAYER

Convolution Layer: Taking the words in happens in various "permutations" and not "combination" as the order matters here. This twisting of arrangements here is called "convolution".
Each arrangement is actually in the form of input matrix and each of them are slided over by a filter matrix, or say dot product and then compared with feature matrix derived from training.



DEEPTEXT ALGORITHM- CNN LAYERS

https://www.aclweb.org/anthology/W18-5408.pdf

RECTIFIED LINEAR UNIT (RLU) LAYER

There is feature matrix which is formed while training the model.

The matrix formed in the convulation layer is compared with the feature matrix to form something called feature map. It indicates how much is the similarity with the feature matrix.

POOLING LAYER

Combinations with similarity less than the threshold percentage with any intent (understand this as intention category) are eliminated. Threshold generally varies from 72%-80%

Threshold in the reference is 75%

Understanding Convolutional Neural Networks for Text Classification

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Abstract

We present an analysis into the inner workings of Convolutional Neural Networks (CNNs) for processing text. CNNs used for computer vision can be interpreted by projecting filters into image space, but for discrete sequence inputs CNNs remain a mystery. We aim to understand the method by which the networks process and classify text. We examine common hypotheses to this problem: that filters, accompanied by global max-pooling, serve as

two concrete tasks: Given a trained model, *model interpretability* aims to supply a structured *explanation* which captures what the model has learned. Given a trained model and a single example, *prediction interpretability* aims to explain how the model arrived at its prediction. These can be further divided into white-box and black-box techniques. While recent works have begun to supply the means of interpreting predictions (Alvarez-Melis and Jaakkola, 2017; Lei et al., 2016; Guo et al., 2018), interpreting neural NLP models re-

DEEPTEXT ALGORITHM- CNN LAYERS

https://arxiv.org/pdf/1509.08967.pdf

FLATTENING

Converts the matrix from pooled feature map into Linear vector.

FULLY CONNECTED LAYER

Linear vector is then pushed to this layer to carry out clustering based on the Euclidian distance and thereby understanding the category and meaning of the text.

Doing all of this text understanding in 20 Languages is not an easy task.

VERY DEEP MULTILINGUAL CONVOLUTIONAL NEURAL NETWORKS FOR LVCSR

Tom Sercu[1,2] *Christian Puhrsch*[1] *Brian Kingsbury*[2] *Yann LeCun*[1]

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ABSTRACT

Convolutional neural networks (CNNs) are a standard component of many current state-of-the-art Large Vocabulary Continuous Speech Recognition (LVCSR) systems. However, CNNs in LVCSR have not kept pace with recent advances in other domains where deeper neural networks provide superior performance. In this paper we propose a number of architectural advances in CNNs for LVCSR. First, we introduce a very deep convolutional network architecture with up to 14 weight layers. There are multiple convolutional layers before each pooling layer, with small 3×3 kernels, inspired by the VGG Imagenet 2014 architecture. Then, we introduce multilingual CNNs with multiple untied layers. Finally, we introduce multi-scale input features aimed at exploiting more context at negligible computational cost. We evaluate the improvements first on a Babel task for low resource speech recognition, obtaining an absolute 5.77% WER improvement over the baseline PLP DNN by training our CNN on the combined data of six different languages. We then evaluate the very deep CNNs on the Hub5'00 benchmark (using the 262 hours

Net") which obtained second place in the classification section of the Imagenet 2014 competition. The central idea of VGG Net is to replace large convolutional kernels by a stack of 3×3 kernels with ReLU nonlinearities without pooling between these layers; The authors argue the advantage of this is twofold: (1) additional nonlinearity hence more expressive power, and (2) a reduced number of parameters. Using these principles, very deep networks are trained with up to 19 weight layers (of which 16 are convolutional and 3 fully connected). By contrast, the classical CNNs deployed in LVCSR have typically only two convolutional layers, use large (9×9) kernels in the first layer, and use sigmoid activation functions. The first goal of this work is to adapt the VGG Net architecture to LVCSR. Most closely related to this is [19], which also uses VGG Net-inspired CNNs for LVCSR[1]. In contrast to our work, the architectures investigated in [19] are quite different and the paper only provides results from training on a non-standard Switchboard-51h dataset, with WER not close to state of the art performance on Hub5'00.

KNOWING THE TARGET AUDIENCE

- Based on the understanding of what users are writing, the content they are liking, sharing, hashtags etc. DeepText understands the user's preferences.

- Based on these preferences, Facebook targets the audience and shows them the articles, posts, status and paid contents they would “most likely ” to prefer.

- However, there have been accusations of using this for "**psychographic targeting**" of ads and campaigns. A company named Cambridge Analytica forked a scandal when they were able to access data of 50 million Facebook users and "may" have used for 2016 Election campaign in US.

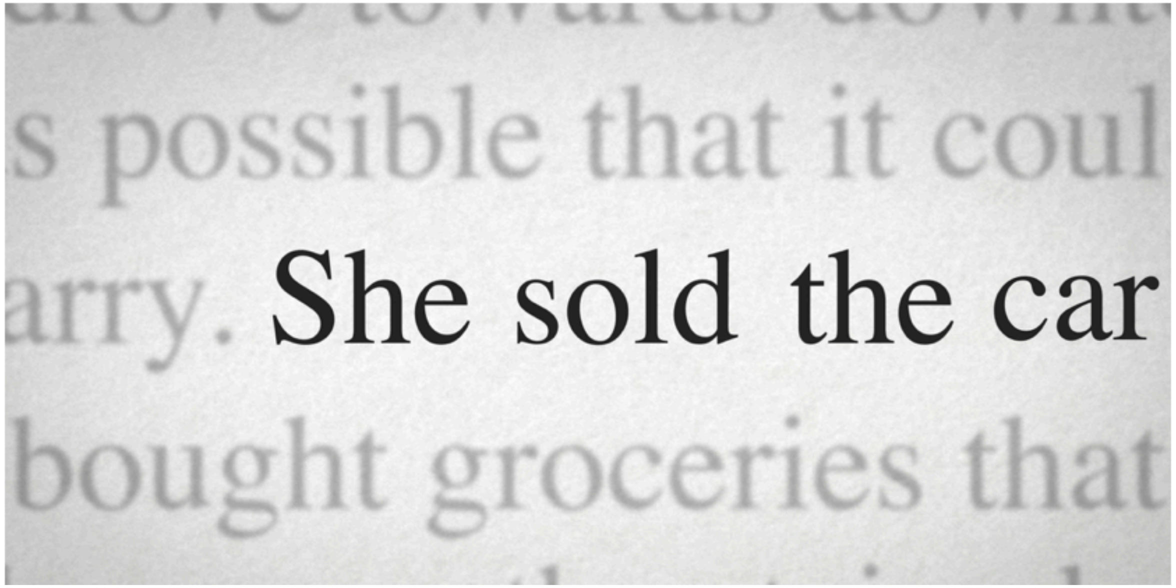
- With DeepText, Facebook is virtually reading everything that you write or like or comment and knows everything about you, possibly even more than know about your preferences.

facebook Engineering

Open Source | Platforms | Infrastructure Systems | Physical Infrastructure | Video Engineering & AR/V

POSTED ON JUN 1, 2016 TO AI RESEARCH, CORE DATA, ML APPLICATIONS

Introducing DeepText: Facebook’s text understanding engine



DEEPTEXT ALGORITHM – APPLICATIONS

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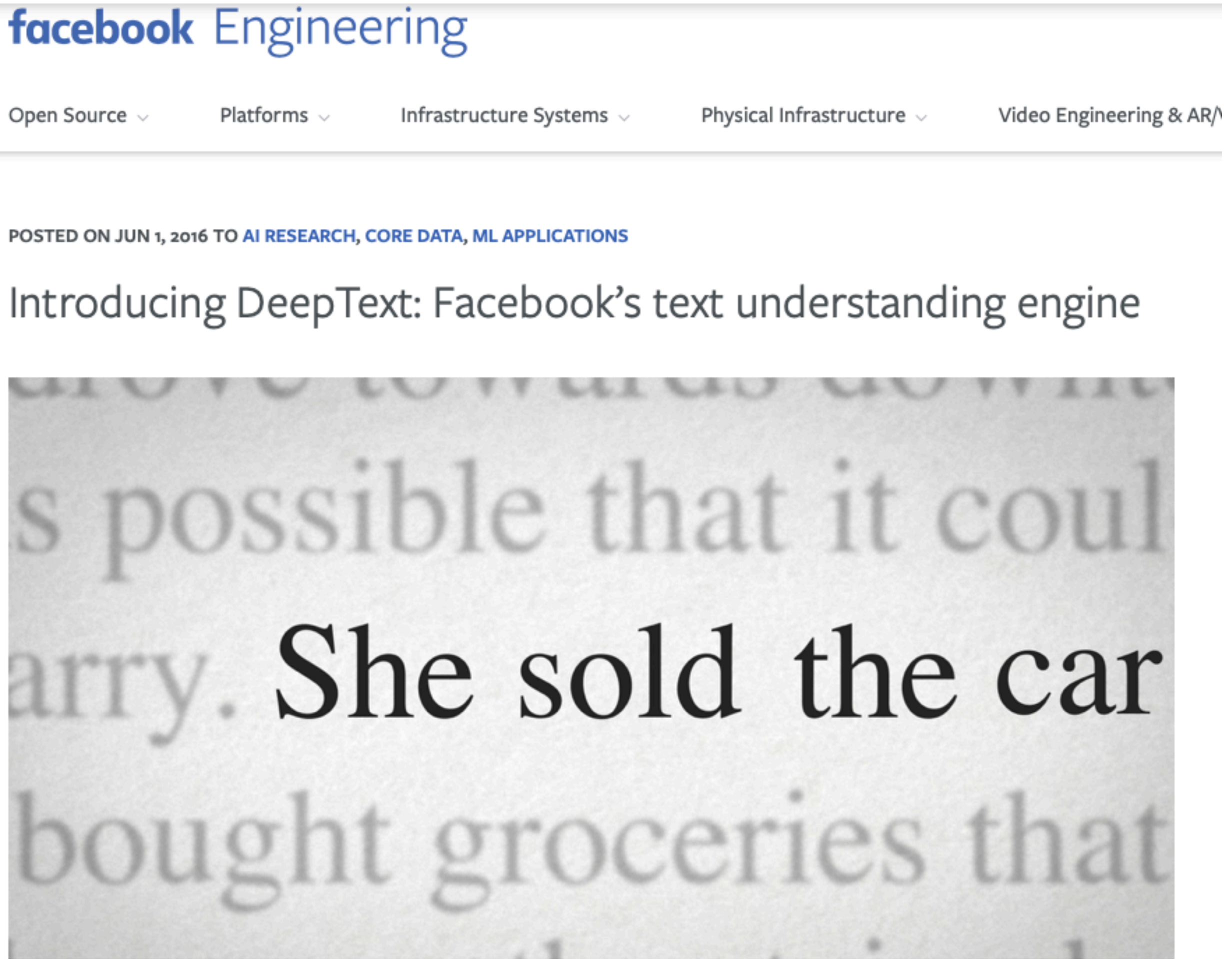

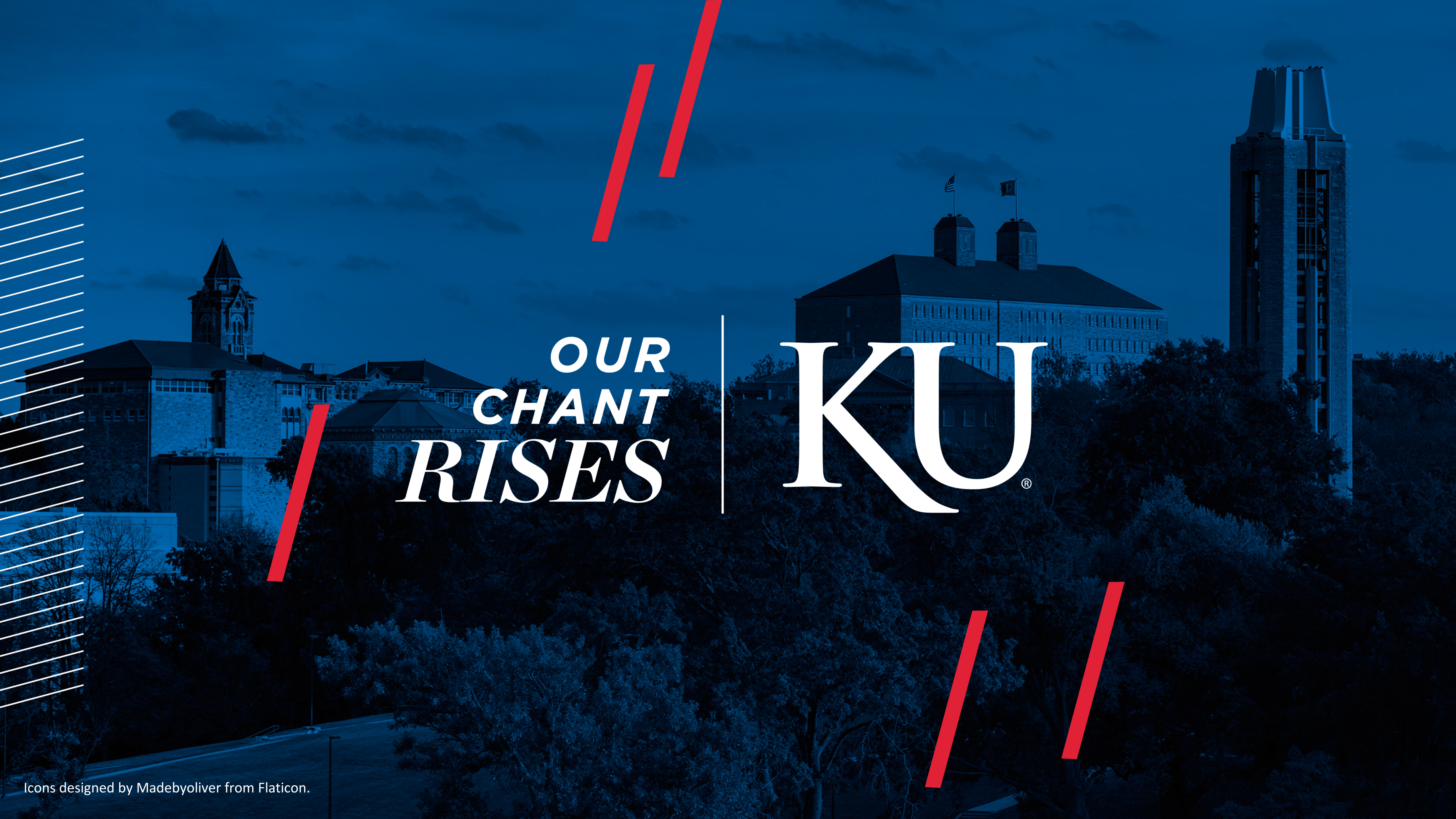
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