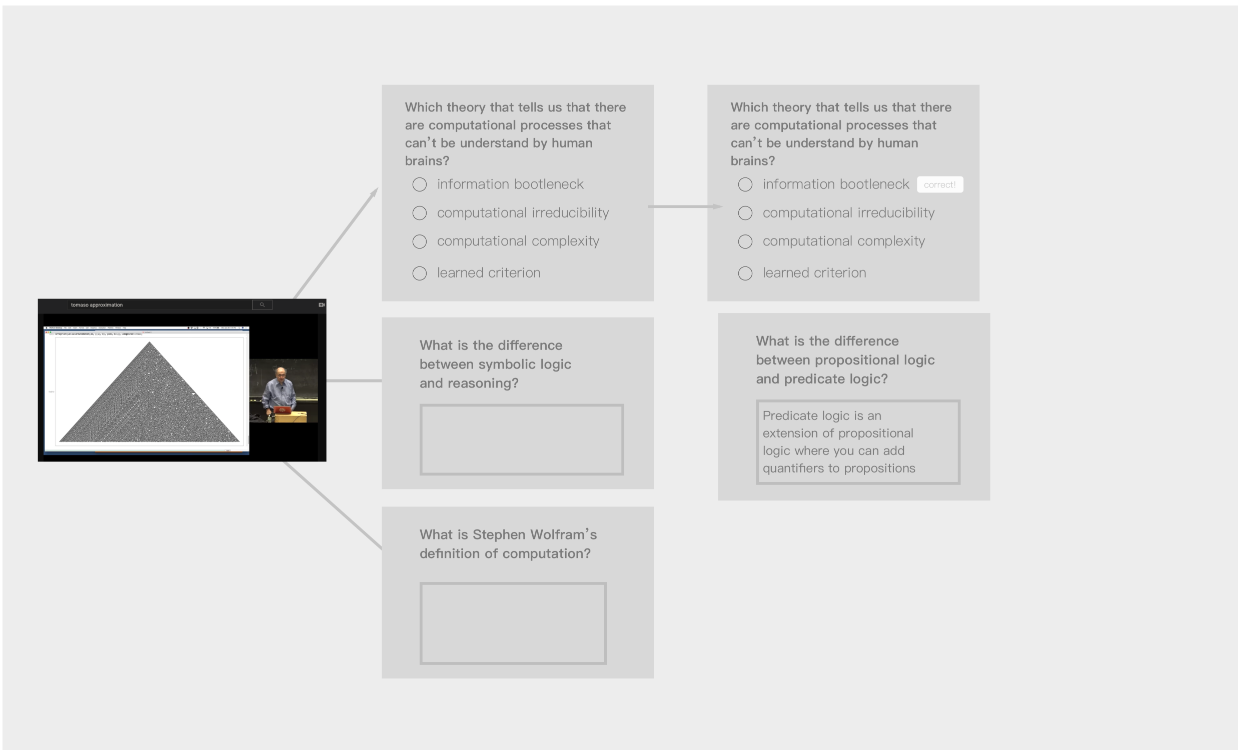
Knowledge Ecosystem - Deep Learning and Education

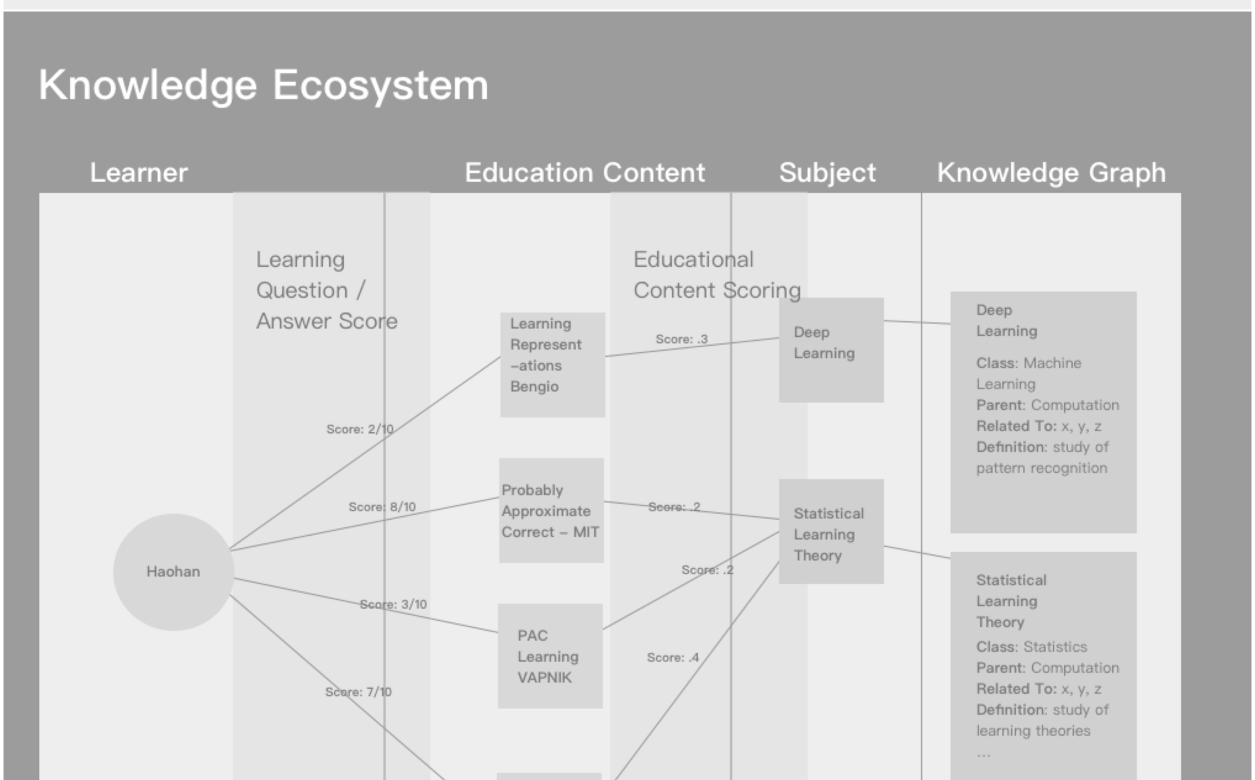
Fanli Zheng (Christian) & Haohan Wang

[DRAFT] 2018-11-19

Contents

Preface


Which theory that tells us that there are computational processes that can't be understand by human brains?
information bootleneck
computational irreducibility
computational complexity
learned criterion
Which theory that tells us that there are computational processes that can't be understand by human brains?
information bootleneck
correct!
computational irreducibility
computational complexity
learned criterion
What is the difference between symbolic logic and reasoning?
What is the difference between propositional logic and predicate logic?
Predicate logic is an extension of propositional logic where you can add quantifiers to propositions
What is Stephen Wolfram's definition of computation?


Knowledge Ecosystem
Learner
Education Content
Subject
Knowledge Graph
Learning Question / Answer Score
Educational Content Scoring
Haohan
Score: 2/10
Score: 8/10
Score: 3/10
Score: 7/10
Learning Represent -ations Bengio
Probably Approximate Correct – MIT
PAC Learning VAPNIK
Score: .3
Score: .2
Score: .2
Score: .4
Deep Learning
Statistical Learning Theory
Deep Learning
Class: Machine Learning
Parent: Computation
Related To: x, y, z
Definition: study of pattern recognition
Statistical Learning Theory
Class: Statistics
Parent: Computation
Related To: x, y, z
Definition: study of learning theories
...

Email Address *

Chapter 1

Introduction

1.1 A Future

Let's start with a future view of an individual's education. Many of us have used the internet to educate ourselves with the abundance of medium to high quality videos, papers, articles, podcasts and how-tos being uploaded from numerous individuals, groups, and institutions like never before (60 hours of video are uploaded to youtube.com every minute).

Let us imagine that all of what you have learned online, throughout the entirety of your life, from the hundreds of Youtube videos, Wikipedia articles, Nature papers, and podcasts you've read, watched, or listened to, were all added structurally to your **knowledge journey**, and what if that journey could be consolidated into what we might call a **knowledge footprint** that could be shared with others? Could this replace static degrees? Or augment them to be more inclusive of a learner's true knowledge? How might we test such knowledge? Could we even predict and provide the guidance on what an individual should be learning next to best support their knowledge acquisition?

1.2 A Comparison

Now, let's go back to our current approach to education. Many of us treat knowledge acquisition like a chapter in the individual's life that is limited to one or more formal places i.e. universities. This is misleading since we accrue knowledge from everywhere and most recently the internet has become a primary source of knowledge acquisition but has gone mostly unaccounted for in terms of recognition (i.e. watching a whole series of Youtube lectures on the Neurobiology of Depression or Discrete Mathematics goes mostly unnoticed when someone views one's resume or by simply looking at their degree). The current approach makes it much harder for people to switch to working and exploring the domains or professional fields outside of their degree area. Knowing rigourous mathematics and not having a degree in it, is said to be surprising, therefore the current "thumbnail view" of an individual's knowledge is necessarily inadequate to the new mediums of knowledge acquisition.

The ideas behind this *knowledge ecosystem*, presents only one of many possible solutions to bringing our education system into modernity. The goal of it would be to promote the long held idea of the **life-long learner**. Moving away from the "education chapter"" of an individual's life to the individual as an evolving learner; learning the necessary skills for what life presents them with today or might tomorrow. It would (combined with traditional education) show us a more accurate depiction of a learner's knowledge and therefore that of a society's collective knowledge.

Visualised over time, we could begin to capture a learner's so called **knowledge journey**. Composed of every piece of content they've gained knowledge from mapped to the *human knowledge graph*. Showing how

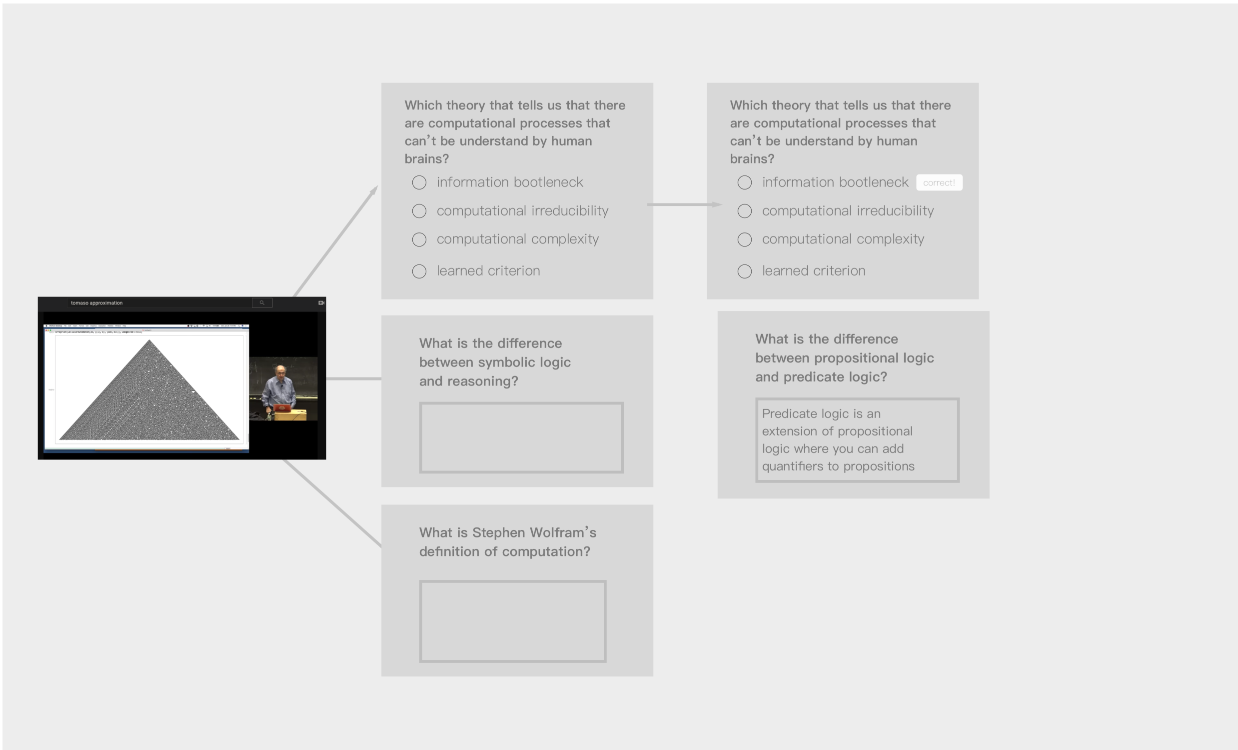


Figure 1.1: EC2QA Network

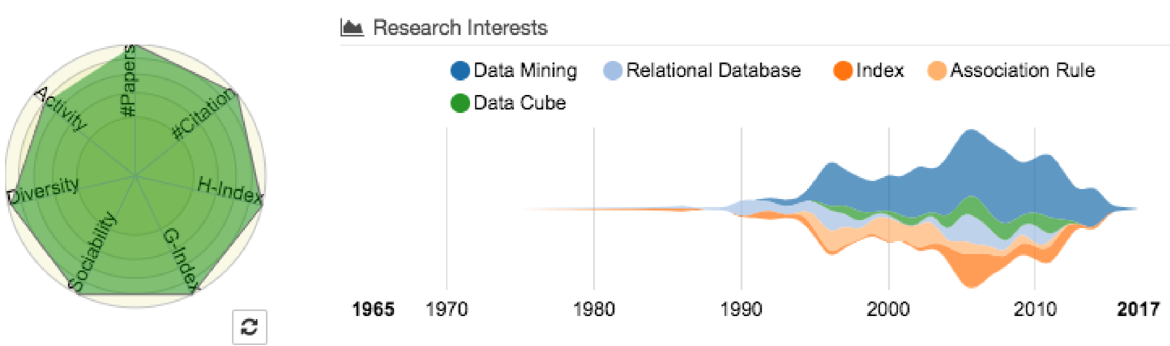


Figure 1.2: Example at aminer.com

an individual has traversed through the world of human knowledge.

This would also serve as a way for others, who may be on a similar **knowledge journey** to connect with "their" cohort which may not need to be bounded by geography or demography. This could be the start of meetups, study groups, flexible class models and so on.

For those who are looking for a change, they may find different journeys that help them decide what step to take next. You would also be able to connect someone's occupation to their **knowledge journey**.

On aggregate, we could begin to cluster similar **knowledge journeys** through unsupervised learning, which might lead to completely new journeys that others may be inspired to follow.

1.3 Knowledge Ecosystem

In this essay, we will propose a **knowledge ecosystem**, a new way of approaching education that attempts to build a more accurate depiction of a learner's true knowledge. It will require significant effort to bring to life but we believe the benefits will outweigh the costs. We will talk about how we can use machine learning, deep learning in particular, to help create and support a **knowledge ecosystem** which is made up of the learner's **knowledge footprint**, **knowledge journeys**, and a **collective human knowledge graph**. We will introduce current advances in deep learning that would enable us to take the space of unstructured educational content on the web and do the following,

- classify content to higher level subjects
- map content unto the human knowledge graph
- test a learner's knowledge of recently viewed educational content through questions and answers, no what matter the subject.

We will also argue that this imagined future is not only **desirable** for society but something similar is required to ensure individual's knowledge are well represented in a time where the pace of change is rapidly speeding up.

Let us not forget, that even software engineering is currently being recreated with machine learning as a key pillar which wasn't much of a thought 5-10 years ago.

It is going to be tantamount if we have an adaptive systems that can represent our current knowledge and also make us predictable to others given the future pushes us to knowing more than ever and knowing who to collaborate with to apply such knowledge.

This hypothetical future isn't just conceptual, most of what we will present to you today is currently feasible due to the most recent advances in machine learning, and in particular deep learning

In the last section of this essay I will review what has been proposed and also call other researchers, teachers, and designers to collaborate on such an ecosystem, even if it is just in part.

*Note: For the purpose of this essay we will talk mostly about digital knowledge acquisition and leave the reader to extend the basics to knowledge obtained elsewhere.

Chapter 2

Primary Concerns

There are 3 main concerns that we will attempt to address in this article about online knowledge acquisition that stand in the way of having an adaptive and reliable knowledge ecosystem. We will attempt to present a system that can sufficiently overcome each of the concerns here and in the implementation section.

There are as follows:

- **Passive Consumption -** most of online content is viewed passively by the learner and the result of passive consumption is that learner's do not grasp the concepts or master the content being taught.
- **Untested Knowledge -** even if the learner was engaged while viewing a piece of educational content their knowledge is untested and therefore it isn't clear if they've mastered the content accurately and in some sense holistically.
- **Knowledge Representation -** even if the learner was engaged (1) and their knowledge was tested (2), simply knowing the counts or types of video they watched doesn't make their knowledge predictable and useful to others. In fact, even the learner may be unaware of all of what they've viewed.

2.1 Passive Consumption and Untested Knowledge

How would such an ecosystem insure us against passive consumption?

Scenario #1 A learner goes online and begins watching a series on Machine Learning. How do we engage and test a user's knowledge?

Proposition: Using advances in deep learning, we propose a dual question and answer generation framework given the educational content.

Result: A learner gets a set of questions and multiple choice answers throughout the video. Keeping the user engaged and sharp to ensure they can answer each of the questions.

As you can see, we've bundled passive consumption and untested knowledge because our proposed ecosystem approaches both of these by always testing knowledge. We will show the current research results in deep learning in the implementation section.

2.2 Knowledge Ecosystem Example

Given a piece of educational content, our knowledge system will generate a set of questions and answers that theoretically capture the major concepts and facts that the learner should know after viewing a part or the content in whole.

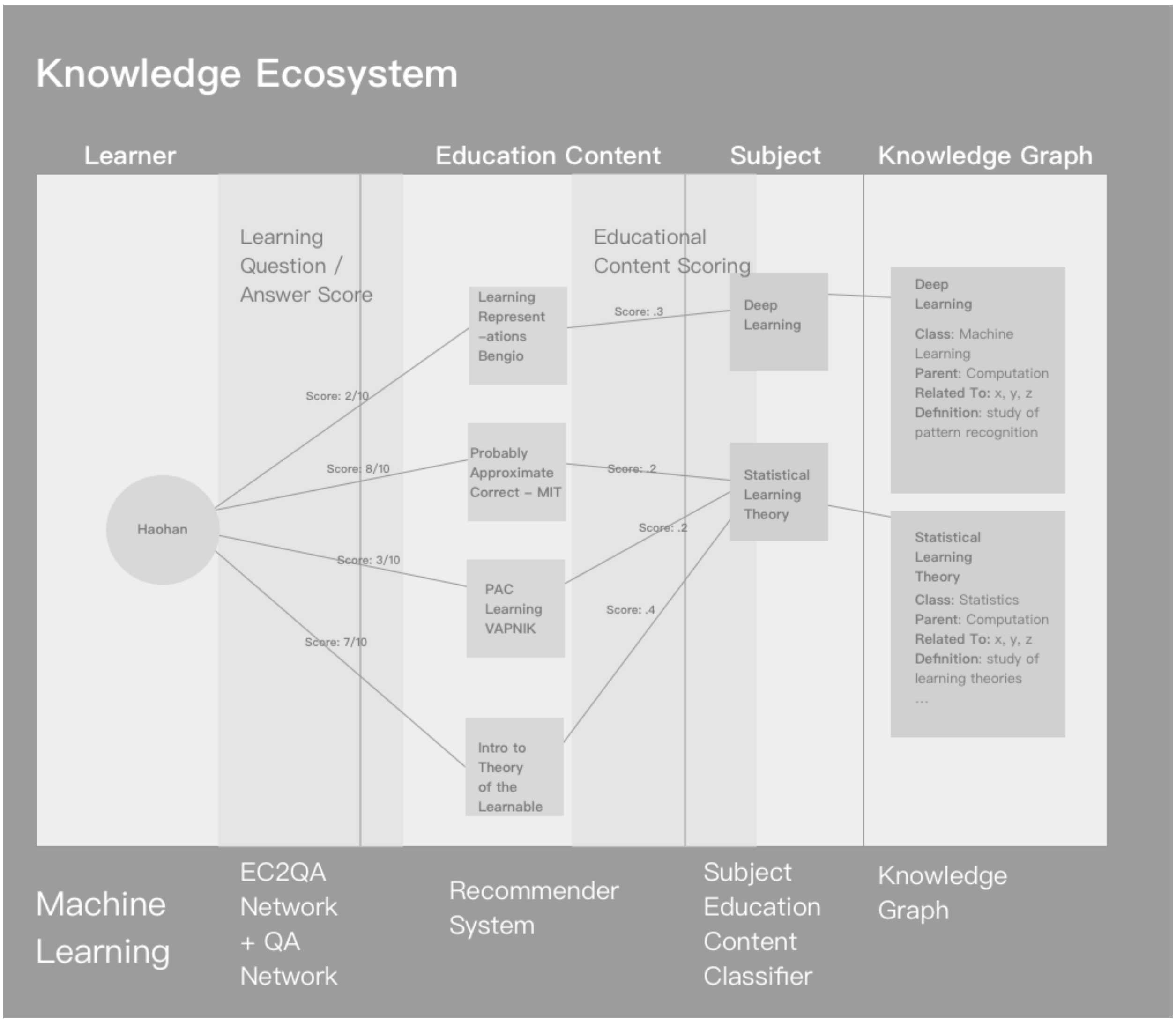


Figure 2.1: Knowledge Ecosystem

You can imagine watching a Youtube video and after a learner views 15 minutes of an hour long lecture on computational complexity a quiz is presented (i.e. a set of questions and answers conditioned on the past 15 minutes of video), and the results are recorded. In the future we would also be able to use the knowledge graph to bring in learner's existing knowledge in order to generate more complex questions and answers based on his/her previous knowledge and the current educational concepts.

As the first step, our knowledge system would only consider content that has been watched with some engagement for now.

2.3 The Problem of Knowledge Representation

> Given most learner's online knowledge acquisition varies and has been invisible up to now, how we can best represent their knowledge?

Scenario #2 A learner has a degree in Public Health, but since graduating, he has been studying machine learning for the last 3 years. The learner now wants to apply to a job that requires Health and Machine Learning. How do we represent their traditional and updated knowledge?

This is a tricky problem that goes beyond any given algorithm. The exact design of a **knowledge footprint** and a **knowledge journey** has been attempted and we will not cover that in depth here. The proposed system presupposes the design of the knowledge footprint.

There is another problem:

> how do we reduce someone's knowledge (in this case a set of educational content and their respective scores) into a symbol that is representative of his/her current knowledge and could be shared across?

Proposition: We introduce **knowledge journeys** and the **knowledge graph** as a way to make sense and structure a learner's knowledge acquisition. The collective **knowledge graph** will tell us about the subject the learner is studying and we can use this to compare to others and create a relative comparison.

Result: Reducing a learner's **knowledge journey** into a common set of dimensions that makeup into their **knowledge footprint** which would look similar to those with similar journeys.

As a result, the employer, now familiar with the footprints can check the overlap between the current employee's and a prospective employee's to support their decision making.

Chapter 3

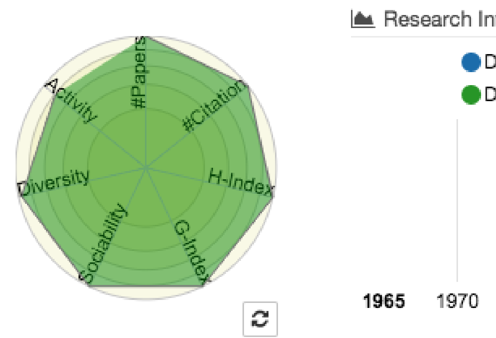
Concepts

As mentioned above, we will be introducing a few novel concepts that we believe are the key components of such an educational ecosystem.

3.1 Knowledge Footprint

The concept of a knowledge footprint is a custom symbol or badge with a profile that represents one's education relative to that of others. This concept is particularly designed for solving the second the knowledge representation concern that we proposed earlier.

In turn, this footprint should be able to represent all of one's education (currently focused on digital) while balancing distinction and commonality with others.



This example from Aminer is a good visual for a knowledge footprint and journey.

3.2 Knowledge Journeys

Image src: https://www.researchgate.net/figure/t-SNE-projection-of-the-embedding-of-all-learners-in-the-dataset-Major-lal fig1_323391033

A **knowledge journey** is a somewhat holistic view of all of the educational content a learner has acquired over time. The journey should be a temporal representation of all of the subjects that one has viewed and been tested on. Knowledge journey should be simple enough to comprehend and compare but complex enough that the individual can go back to any particular moment in time and review the educational content they've viewed before. Coupled with the knowledge graph, it can also shed light on the possible next education content that a learner should be or would be interested learning.

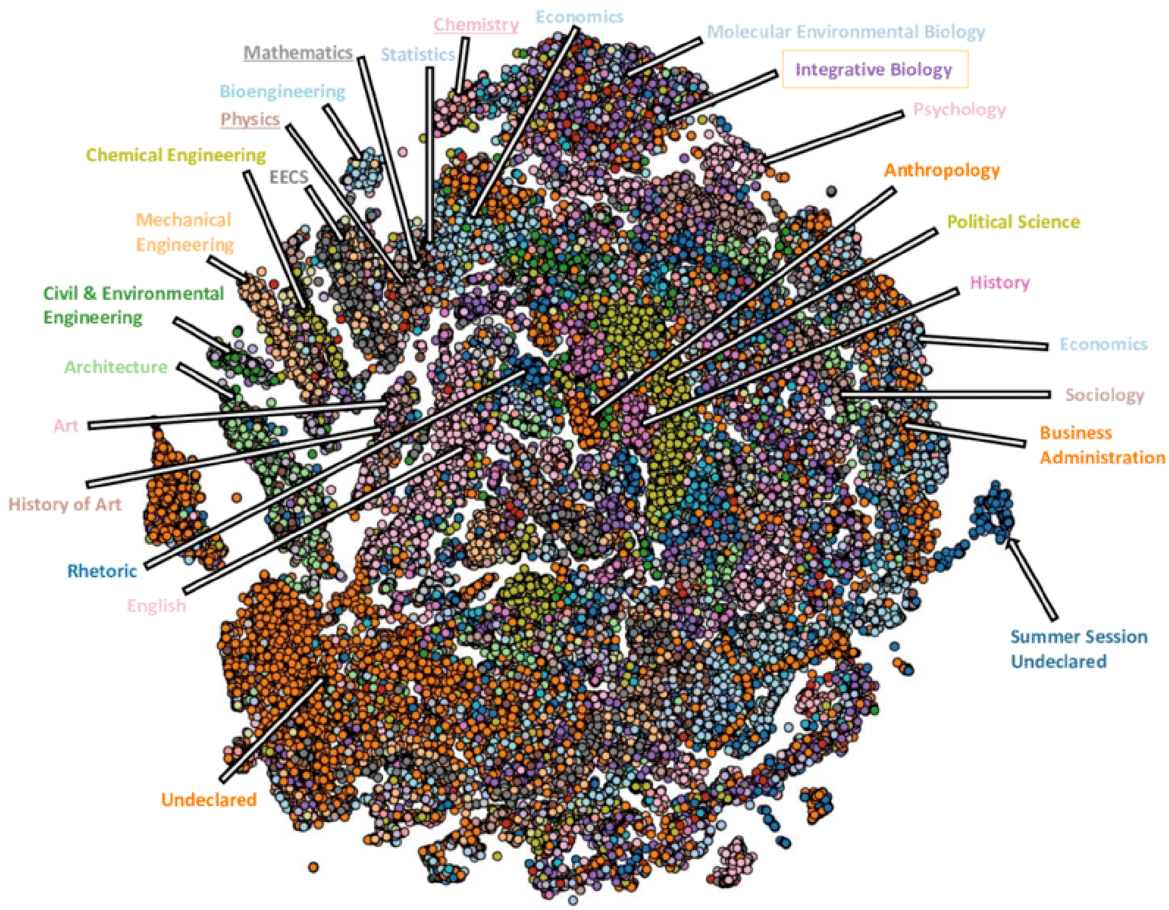


Figure 3.1: Image title

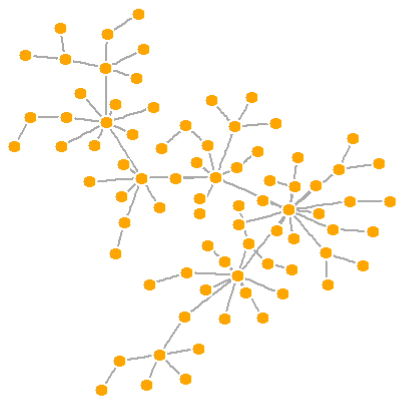


Figure 3.2: Image title

This concept also helps address the knowledge representation concern. This time instead of capturing a consolidated snapshot of one's current knowledge, this concept takes a temporal route to capture one's entire learning path.

3.3 Collective Human Knowledge Graph

The collective human knowledge graph can be compared to Google's Search Knowledge Graph (?) which points unstructured information towards structure. The graph should have all existing subjects that we are currently aware of (i.e. Mathematics, Computer Science, Art, and Sociology, etc). Since each piece of educational content will be classified into one more more sub-subject(s), all subjects will exist in detail within the knowledge graph.

On the other hand, we could also use these subjects that are associated with that piece of content to help create the knowledge footprint for the learner.

3.4 EC2QA Network

We mentioned the EC2QA network earlier because currently we would have to cobble together multiple networks to make this work. Instead we will introduce a novel network framework, EC2QA, to solve the problem of generating questions and answer pairs for any given educational content (text, video, image, pdf, etc).

The possible implementation solutions are introduced in the implementation section.

3.5 Knowledge Ecosystem by Example

Now that we are aware of each of the elements, let's talk about how they work in practice.

A learner watches a video titled 'Depression' by Robert Sapolsky.

- The video is classified by a neural network as the following subjects [Neuroscience, Mental Health, Psychology];
- The subjects are then mapped to the **knowledge graph** which gives us more information about each subject;

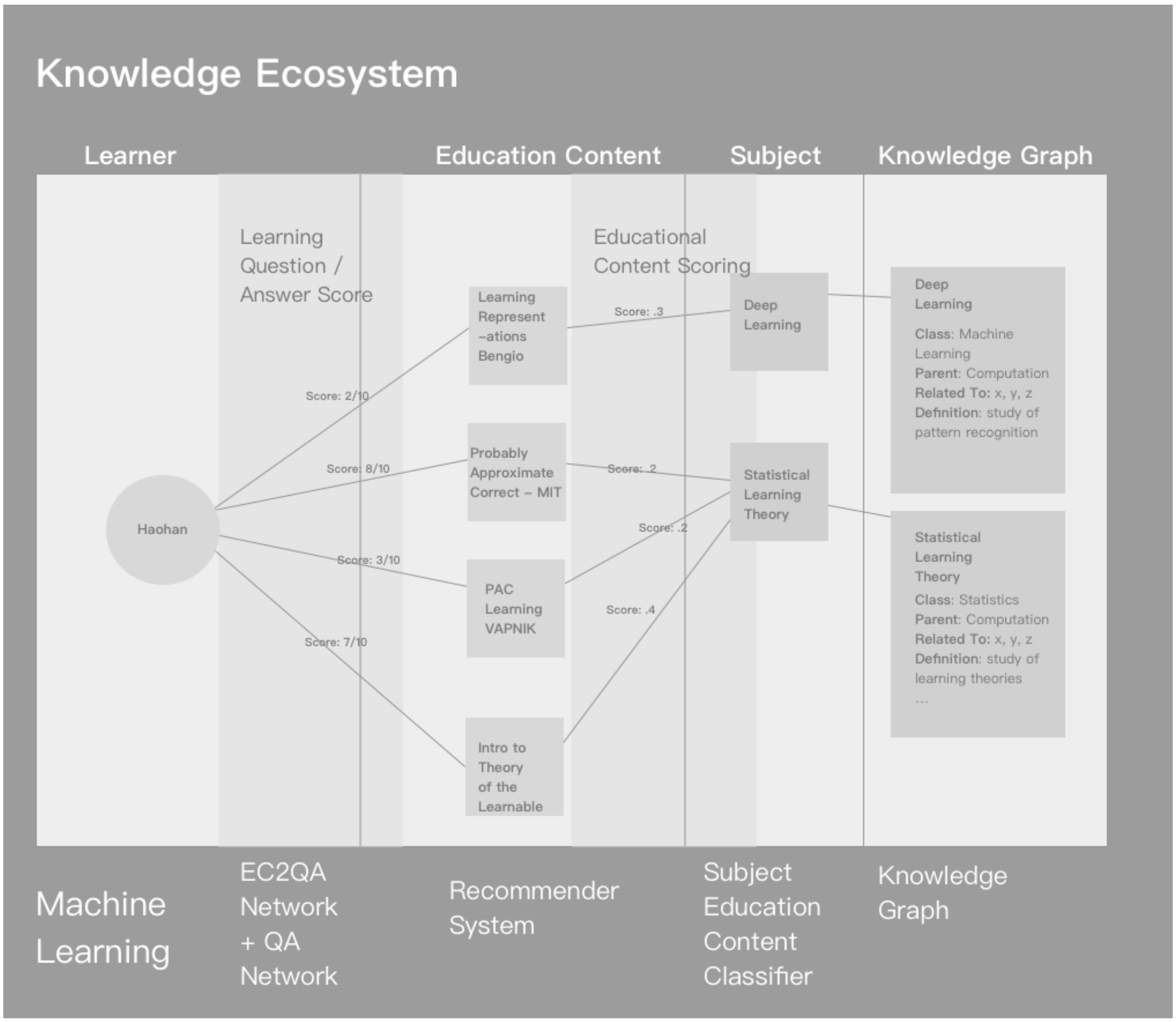


Figure 3.3: Knowledge Ecosystem

- Using EC2QA or similar, a set of questions and answers are generated for every 15* minutes of video;

A learner is present with 5 questions to answer and scores 4/5 (80%).

- The link between user and video takes up the score;

At the end of the video, the learner records a video summary and is evaluated with a score 7/10 (70%).

- The evaluation network looks at the **semantic and conceptual mutual information** shared between the original content and the learner's video summary;
- All scores are mapped to the video and also counted at the subject level;

A learner looks at their knowledge footprint.

- All scores should be calculated against all subjects coming from the knowledge graph and compared against other learners to generate the footprint.

Chapter 4

Implementing the Knowledge Ecosystem

In this section, we set out to answer the following question:

> How might we approach designing such a knowledge ecosystem?

We will take a tour through some possible implementations of the proposed knowledge ecosystem, presenting the relevant research in machine learning for each of the elements of the knowledge ecosystem, We will also discussing a new artificial neural network architecture Educational Content to Question Answer (EC2QA) network and what would be needed to design such a network.

Note that this is not meant to be a fully decided on system, but instead, each of these components can be developed independently and vary from what you find here. This is a provocation for getting started on the knowledge ecosystem today.

4.1 Problem Formulation

Building such a knowledge ecosystem is not a trivial task. A necessary step of searching for the proper solutions would be trying to break the whole system into independent elements that we can deal with separately. As we discussed earlier, we've divided the ecosystem into the elements below:

1. **Learning + Feedback** – given a learner consumes a piece of educational content, reliably evaluate their knowledge and provide the feedback for improvement to support their learning. (credibility, rigour)
2. **Knowledge Graph** – general knowledge blueprint, as a map to piece together all the content that is currently available. (relatibility, predictability)
3. **Knowledge Journeys** – given a piece of educational content, classify it within a knowledge graph; given multiple learner journeys, create a way to customize their own growth journey while offering a way for them them to compare, connect with and follow, other's journey (compare, traverse, curiosity)
4. **Knowledge Footprint** – given a learner's journey, collapse it into a representative symbol(s) (digital education footprint) (relatibility, stable but evolving system)

Much of element two (#2) and all of element three (#1) have been made possible with the recent breakthroughs in machine learning especially in the field of deep learning. A few other pieces like element #3 and #4 may require a different approach to tie the other elements together and has not been proposed yet to. We see #3 and #4 as design problems that should be approached from the bottom up. Therefore, in this section we will be primarily focus on the first two (#1 & #2) elements.

4.1.1 Before we start...

As discussed above, recent trends in deep learning have produced state-of-art results on relevant tasks that we will cover below.

To best illustrate the problem and possible solutions, we could focus on the whole space of different types of educational content ranging from text to podcasts, but we will focus solely on taking educational videos (Youtube or how-to videos). Videos not only happen to be complex, but they are also one of the richest media types for knowledge acquisition. Keep in mind that our ultimate goal is to apply our approach to any type of online educational content including open texts, digital texts, audio or podcasts.

Let us now explore some of the recent results that would enable us to design the first two(#1 & #2) elements of our ecosystem.

4.2 Learning + Feedback

4.2.1 Primary concerns

We consider learning + feedback as a key building block of the ecosystem which would settle our concerns with online content assumption being passively consumed and the information is untested and may not be regarded as true knowledge even if the learner watched the lecture completely.

4.2.2 Question Formulation

In short, in this section we will be providing some insights on how to solve the following puzzle:

> "how can we take a single educational content and properly test a learner's knowledge while also providing insightful feedback to support their learning?".

4.2.3 The Approach

Based on the above concerns we'll have to ensure that our learning and feedback element can do the following

1. Generate a set of questions and answers for any educational content (Domain: Question and Answer Generation)
2. Evaluate closed and open ended answers (Domain: Answer Evaluation)
3. Provide a score for the content based on the learner's performance (Domain: Aggregate scoring)

The ideal result would provide a learner with a credible picture of their tested knowledge and an interactive learning experience that better supports knowledge acquisition.

We will now explore current research trends in deep learning that will help us solve the problem.

In previous years, deep learning research has taken up a similar problem titled Question Generation (QG) and Question Answering (QA).

Question & Answer Generation

Question Generation (QG) was originally part of NLP. The goal of QG is to generate questions according to some given information. It could be used in many different scenarios i.e. generating questions for reading comprehension, generating data from large scale question-answering pairs or even generating questions from images. Earlier approaches to QG mainly used human-crafted rules and patterns to transform a descriptive sentence to a related question. Recent neural network-based approaches represent the state-of-art of most of those tasks and this approach has been successfully applied to many other NLP tasks i.e. neural machine translation, summarization, etc. As the training optimization studies progress, the stability and performance improvements are guaranteed.

As for Question Answering (QA) task, it is a well-researched problem in NLP as well. Recently, QA has also been used to develop dialog systems and chatbots designed to simulate human conversation. Traditionally, most of the research used a pipeline of conventional linguistically-based NLP techniques i.e. parsing, part-of-speech tagging and coreference resolution. However, with recent developments in deep learning, neural network models have shown promise for QA. Further improvement i.e.attention mechanism and memory networks allow the network to focus on the most relevant facts such that they achieved state-of-art performance for QA.

Now we have some basic understanding of these 2 problems for which we will be expanding more in depth later. Consider the next question:

> “what types of questions & answers would be best to test a learner’s knowledge given a piece of educational content (i.e. a lecture video)”

Let’s say a learner is watching a video about hypothesis testing, midway through the video the educator shows an example and provides the data needed to test the hypothesis. It would be ideal if during this time the learner’s knowledge is tested with the following possible questions:

1. What is the definition of the p-value? (and provide multiple choices for learner to choose from)
2. Is this a 1-sided test? (answers provided would be: YES or NO)
3. How would you interpret the p-value in the context of this example.
4. What is the difference between null hypothesis and alternative hypothesis based on your understanding?
5. Tell me what you have learned through this video or this example. (It is also helpful to ask learner the question as follows after showing the solution)

As shown above, we would call questions #1 and #2 the close-ended questions; question #3 and #4 the specific open-ended questions; and question #5 a general open-ended question.

Based the above information, we can update our question formulation into:

1. Generate close-ended question + answers pairs
2. Generate specific open-ended question + answers pairs
3. Evaluate and comment on the general open-ended answers

In terms of the close-ended, the answers can be well defined and evaluated. However, the process might be a little bit tricky when it comes to the open-ended questions. We will approach each of them here from the current research perspective.

4.2.3.1 ** Why deep learning? **

As we stated above, deep learning has achieved state-of-art performance in both QG and QA tasks. But how?

If you pay close attention to the question generation and answer generation type of problems, you can easily reframe this problem into a general machine learning problem in which the model needs to learn the relationship between the educational content and the meaningful question & answer pairs that is associated with the content. In other words, our problem could be simplified as learning a function that is capable of capture the relationship between our input and output, or, appropriately map the educational content to the desired question and answer pairs with this function.

To the best of our knowledge, deep learning is one of the most optimal techniques currently developed to learn such complex representations of complex data such as video lectures.

By definition, machine learning is subfield of Artificial Intelligence that uses statistical learning techniques to give the machine the ability to learn from the data. It explores the algorithms that can be used to parse data, learn from the data, and then apply what they have learned to make intelligent decisions. Or more specifically, deep learning is a subset of machine learning that belongs to the family of representation learning. Inside this family, deep learning is particularly good at sampling the features and having additional layers for more abstract feature learning. All of these features are crucial for our goal of mapping the feature to the output task.

Because of the above advantages, deep learning is known as one of the most flexible machine learning algorithms that can learn and map a **deep representation** of supervised concepts within the data. Deep neural network architecture can be composed into a single differentiable function and trained end-to-end until it converges. As a result, they can help identify the suitable *inductive biases* catered to the training data.

Moreover, deep learning outperforms other techniques when the training data is large and the advantage fits our situation well. We could easily find a large amount of educational content available on the web.

The large amount content creates another problem that can be avoided with deep learning, which is it's going to be very troublesome if you plan to do feature engineering manually. When there is lack of domain understanding for feature introspection, deep learning is preferable.

In the end, deep learning really shines when it comes to many specialized research problems such as NLP, Visual Recognition and Speech recognition. For solving our task, all those domains will possibly be involved.

4.2.4 Question Generation

Let's begin with question generation (QG) problem.

The ideal goal of an automatic question generation is to generate a question Q that is syntactically and semantically correct, relevant to the context and meaningful to answer.

In order to achieve this goal„ we need to train an algorithm to learn the underlying conditional probability distribution

$$P_\theta(Q|X)$$

parametrized by θ. In other words, we can think of this problem as the one that requires the model to learn a function (with a set of parameters) θ during the training stage using content-question and/or answer pairs so that the probability $P_\theta(Q|P)$ is maximized over the given training dataset.

It is also helpful to frame this problem into a seq2seq learning problem since both the input and the output are most likely a sequence of text character that the model needs to process and learn the relationship from.

4.2.4.1 Case Studies

1. In this paper QG-Net: A Data-Driven Question Generation Model for Educational Content. They use a bi-directional LSTM network to process the input context words sequence. Encoding the answer into context word vectors.

QG-Net generates questions by iteratively sampling question words from the conditional probability distribution $P(Q|C, A, \theta)$ where θ denotes the set of parameters. In order to construct the probability distribution, they first create a **context reader** that process each word c_j in the input context and turns it into a fix-sized representation h_j

Then, they used a **question generator** generates the question text word-by-word, given all context word representation and all question words in previous time steps.

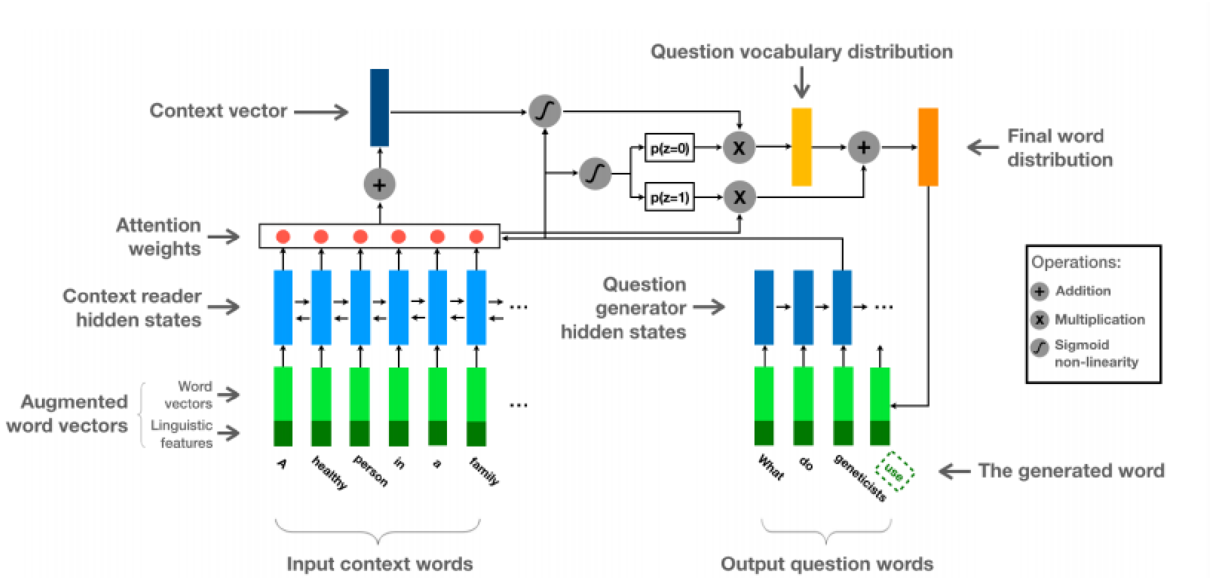


Figure 4.1: ma

As for the quantitative evaluation, they aimed to minimize the difference between the generated question and the true question in the training set during training. Also, they used the standard back-propagation through time with the mini-batch stochastic gradient descent algorithm to learn the model parameters. They employed teacher forcing procedure for training LSTMs. To enhance performance, they also implemented beam search, a greedy but effective approximation to exhaustively search and select the top 25 candidate output question sentences. The final one would be the one with the lowest negative log likelihood.

The general QG-Net model Architecture is as below:

2. In this summary Learning to Ask, they used a sentence- and paragraph-level seq2seq model to read text from the input content and to generate a question about the input sentence.

For the second option, we need to encode both sentence and paragraph that sentence belongs to as input, but only attending source sentence hidden states. The performance could be improved with beam search and UNK replacement.

3. In this paper TOPIC-BASED QUESTION GENERATION, they proposed a topic-based question generation algorithm. The algorithm will be able to take in a input sentence, a topic and a question type; then generate a word sequence related to the topic, question type and the input sentence.

They are formulating a conditional likelihood objective function to achieve this goal.

Also, in the paper, they proposed a few frameworks that were used to tackle this problem. The first type is seq2seq model. This model typically uses a bidirectional LSTM as the encoder to encode a sentence and a LSTM as the decoder to generate the target question.

The second approach is question pattern prediction and question topic selection algorithms. It takes in an automatically selected phrase Q and fill this phrase into the pattern that was predicted from pre-mined patterns, which is not done with deep learning.

The last approach is multi-source seq2seq learning which aims to integrate information from multiple sources to boost learning.

4. In this paper A Framework for Automatic Question Generation from Text using Deep Reinforcement Learning they proposed a novel way of solving this problem in which they used a reinforcement learning framework that consists of a generator and an evaluator.

They refer to the generator as the *agent* and the *action* of the agent is to generate the next work in the question. The probability of decoding a word $P_\theta(word)$ gives a stochastic policy.

The evaluator will in turn assign a reward for the output sequence predicted using the current policy of the generator. Based on the reward assigned by the evaluator, the generator updates and improves its current policy. The goal in RL-based question generation is to find a policy that can maximize the sum of the expected return at the end of the sequence generated.

4.2.4.2 Summary

In this QG section, we have discussed 4 algorithms. They provide us a way to frame our problem for which we can apply generative seq2seq model framework. As for our objective function, we are formuating a conditional probability distribution that is conditioned on the provided content (i.e. the video) and answers. Typically, we can use a bi-directional LSTM as the encoder to encode the content and use a LSTM as the decoder to generate the question.

However, as you probably have noticed that the above examples are focus mainly on processing the text input data instead of videos directly. It demonstrates that more research in this new area is needed so as to meet our particular needs.

4.2.5 Question Answering

Now, let's move on to our question answering (QA) step. The general goal of a QA model is to predict an answer to the question based on the information found in the passage, given a passage and a question.

Here are the overview of a basic QA model's implementation (**?**):

1. Build representation for the passage and the question separately.
2. Incorporate the question information into the passage.
3. Get the final representation of the passage by directly matching it against itself
4. Generate the answer

And the typical techniques applied for solving such a problem include:

- Embedding
- Encoder Decoder
- Attention Mechanism

4.2.5.1 Close-ended Questions

4.2.5.1.1 Visual Question Answering (VQA)

As what we have covered above, most QG problem focuses solely on generating questions but not the answers based on the context.

VQA is a challenging research problem that focuses on providing a natural language answer given any image and any free-form natural language question. As we are managing to handle the video educational content first that is likely to involve language processing and visual recognition tasks, VQA would be a proper start for us. By leveraging this type of algorithm, we enable our system to easily evaluate the answer provided by learners which could in turn automated the whole question + answering + evaluation cycle.

Since we are dealing with visual input, question-guided attention mechanism is a key component for solving this type of task. Started from the attention mechanism that can adaptively learn the most relevant image regions for a given question. Then to stack multiple question-guided attention mechanisms to learn the attention in an iterative way. Also, it is possible to use bilinear features to integrate the visual features from the image spatial grids with question features to predict attention. Considering the questions in natural language may also contain some noise, the co-attention mechanism can jointly learn the attention for both the image and question.

4.2.5.1.1.1 Case Studies

1. In this paper Deep Attention Neural Tensor Network for Visual Question Answering, they proposed a novel deep attention neural tensor network that can discover the joint correlation over images, questions and answers with tensor-based representation.

As for their workflow, they modeled one of the pairwise interaction (i.e. between image and question) by bilinear features, which is further encoded with the third dimension (i.e. answer) to be a triplet using bilinear tensor product. During this step, the model takes in a question + a corresponding image + candidate answers as the input. A CNN (convolutional neural network) a GRU RNN (recurrent neural network) are used for extracting feature vectors and question respectively. Then the representation is passed on as a multi-modal features and integrated by bilinear pooling module. Moreover, they decompose the correlation of triplets by their question and answer types with a slice-wise attention module on tensor to select the most discriminative reasoning process inference.

In the end, they optimize the proposed network by learning a label regression with KL-divergence losses. They claimed that with these techniques, they can enable scalable training and fast convergence over a large number of answer set. During the inference stage, they feed the embeddings of all candidate answer into the network and then select the answer which has the biggest triplet relevance score as the final answer.

The high-level network architecture is as follows:

2. In this paper Question Type Guided Attention in Visual Question Answering, they proposed a model called Question Type-guided Attention (QTA). This model utilizes the information of question type to dynamically balance visual features from both top-down and bottom-up orders.

Finally, they propose a multi-task extension that is trained to predict question types from the lexical inputs during training which generalizes the network into applications that lack question type, with a minimal performance loss.

As for their main contribution, they focus on developing an attention mechanism that can exploit high-level semantic information on the question type to guide the visual encoding process.

Specifically, they introduced a novel VQA architecture that can dynamically gate the contribution of ResNet and Faster R-CNN features based on the question type. In turn, it allows them to integrate the information from multiple visual sources and obtain gains across all question types.

4.2.5.1.2 Video Question Answering

The recent advancements that we discussed above in VQA domain have shown some promising implication. In terms of achieving our particular goal, it is also worth mentioning that VQA might be a good start but it is not sufficient yet. To bridge this gap, let's focus our attention on some video question answering algorithms that have been proposed.

4.2.5.1.2.1 Case Studies

1. In this paper Multi-Turn Video Question Answering via Multi-Stream Hierarchical Attention Context Network, they proposed a hierarchical attention context network for context-aware question understanding by modeling the hierarchically sequential conversation context structure. They also incorporate the multi-step reasoning process fro the multi-stream hierarchical attention context network to enable the progressive joint representation learning of the multi-stream attentional video and context-aware question embedding.

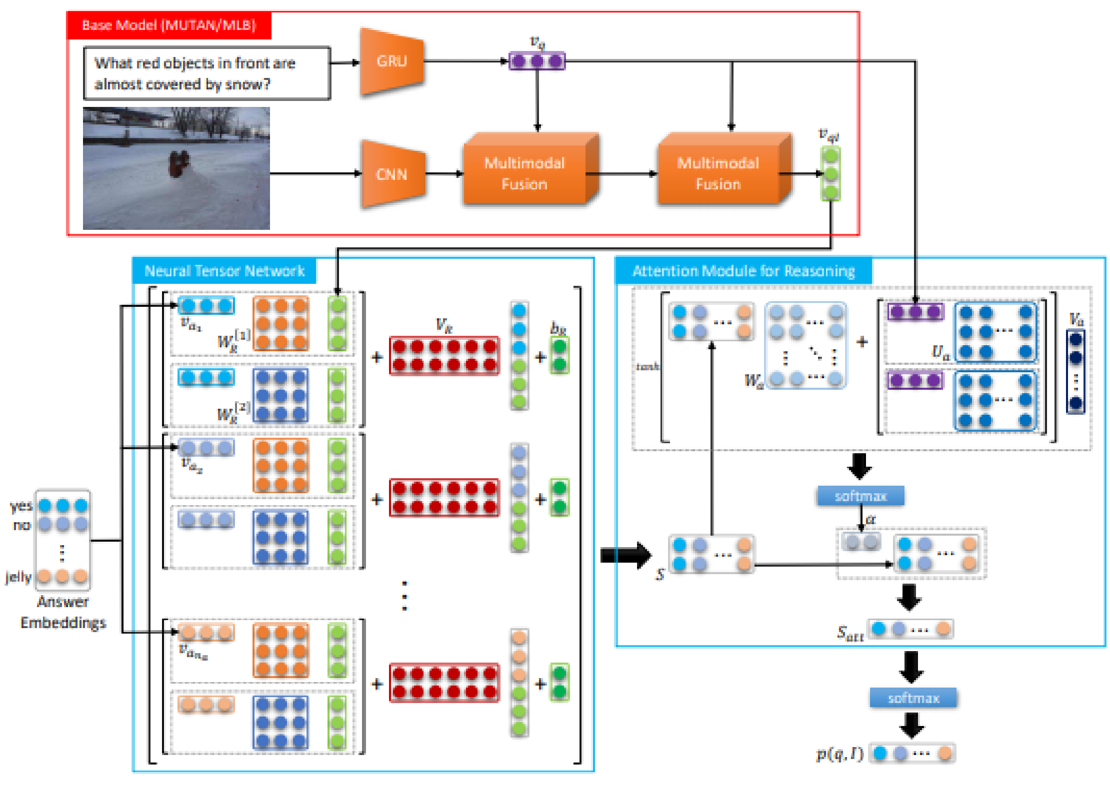


Figure 4.2: Deep Attention Neural Tensor Network

The construct their dataset by collecting the conversational video question answering datasets from YouTube-Clips and TACoS-MultiLevel in which the first one has 1987 videos and the second dataset has 1303 videos. They invite 5 pairs of crowd-sourcing workers to construct 5 different conversational dialogs. In total, they have collected 37228 video question answering pairs for TACoS-MultiLevel data and 66806 ones for YouTube-Clips data.

2. In this paper MovieQA: Understanding Stories in Movies through Question-Answering, they introduced a new dataset called MovieQA dataset that can evaluate automatic story comprehension from both video and text.

They collected 408 subtitled movies and obtained their extended summaries in the form of plot synopses(movie summaries that fans write after watching the movie) from Wikipedia. They used plot synopses as a proxy for the movie. They have annotators create both quizzes and answers pairs by referring to the story plot. Time-stamp is also attached with each question.

In the second step of data collection, they used the multiple-choice answers and question collected as the input to show to the annotators. By doing so, annotators can re-formulate the question and answers while doing the sanity check.

4.2.5.1.3 Summary

By going through the previous examples, we can see that VQA is very particular type of algorithms that is designed to efficiently process image and text input data while making the inference based on the input. Attention is a typical mechanism applied in there type of problems and multiple forms of **huh????** on the attention mechanism used in these models have significantly improved the model performance.

Going from VQA to video question answering algorithm, it has been a great leap. The main insight we can directly draw from these video QA papers is that we can follow their steps to collect and annotate our training data by asking crowd-sourcing workers to construct the question and answer pairs. Also, more advanced algorithm like the one described above multi-stream hierarchical attention context network is in need for dealing with video input data in contrast to static pictures.

4.2.5.1.4 Dual Question-Answering Model

Both Question Generaion(QG) and Question Answering(QA) are well-defined 2 sets of models that aim to either infer a question or an answer given the counterpart based on the context. However, they are usually explored separately despite of their intrinsic complementary relationship. In our case, a system that can take on both roles simultaneously are needed to fully automated learning + feedback process.

There are some algorithms are designed to fulfill both roles.

4.2.5.1.4.1 Case Studies

1.In this paper Dual Ask-Answer Network for Machine Reading Comprehension they present a model that can learn question answering and question generation simultaneously. They tie the network components that playing the similar roles into 2 tasks to transfer cross-task knowledge during training. Then the cross-modal interaction of question, context and answer is captured with a pair of symmetric hierarchical attention processes.

The high-level architecture of the model is illustrate as below:

In short, the model is composed of embedding layer, encoding layer, attention layer and output layer. The model is fed with a question-context-answer triplet (Q,C,A) and the decoded Q and A from the output layer. Their loss function consists of 2 parts:

- negative log-likelihood loss
- a coverage loss to penalize repetition of the generated text

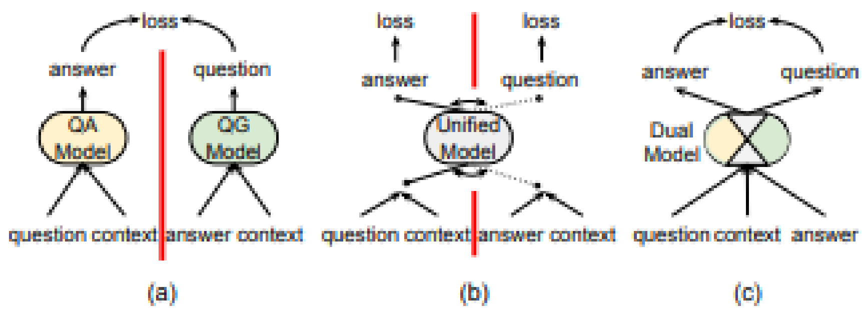


Figure 4.3: Dual Ask-Answer Network 1

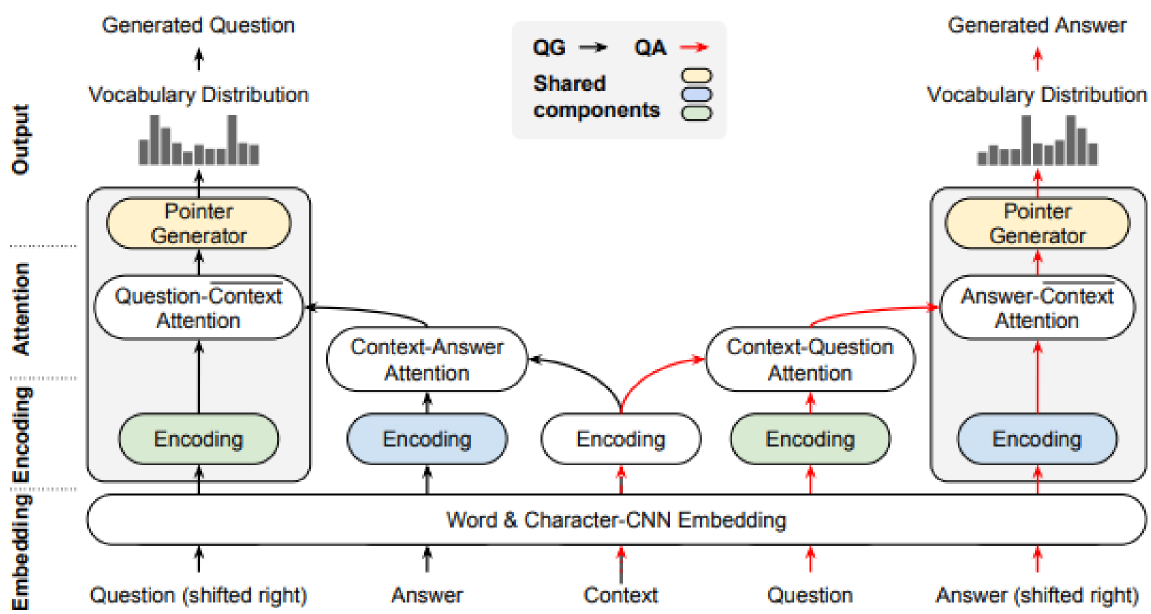


Figure 4.4: Dual Ask-Answer Network 2

2. In this paper Harvesting Paragraph-Level Question-Answer Pairs from Wikipedia, they applied their question-answer pair generation system to 10000 top-ranking Wikipedia articles and create over a million question-answer pairs.

In their task formulation part, they mentioned that they break this task into 2 sub-tasks:

- candidate answer extraction
- answer-specific question generation

To achieve them, they first identify a set of question-worthy candidate answers ans = (A1, A2,...Ai). For each candidate answer Ai, they then aim to generate a question Q - a sequence of tokens y1,y2,...yn - based on the sentence S that contains candidate Ai such that Q asks about an aspect of Ai (of potential interest to a human) and Q might rely on information from sentences that precedes S in the paragraph. Mathematically, they compose a function

$$Q = argmax_Q P(Q|S, C)$$

.

3. In this paper Visual Question Generation as Dual Task of Visual Question Answering, they proposed an end-to-end unified model, Invertible Question Answering (iQAN) to introduce question generation as a dual task of question answering to improve VQA performance.

In achieving their goal, they leverage the **dual learning** framework that is proposed in machine translation area initially, which uses A-to-B and B-to-A translation models to form two closed translation loops and let them teach each other through a reinforcement learning process.

In their VQA component, given a question q, an RNN is used for obtaining the embedded feature $\mathbf{q}$, and CNN is used to transform the input image v into a feature map. A MUTAN-based attention module is then used to generate a question-aware visual feature v_q from the image and the question. Later, another MUTAN fusion module is used for obtaining the answer feature $\hat{a}$

4. In this paper A Unified Query-based Generative Model for Question Generation and Question Answering, they propose a query-based generative model for solving both tasks. The model follows the classic encoder-decoder framework. The multi-perspective matching encoder that they are implementing is a bi-directional LSTM RNN model that takes a passage and a query as input and perform query understanding by matching it with the passage from multiple perspectives; The decoder is an attention-based LSTM RNN model with copy and coverage mechanism. In the QG task, a question will be generated from the model given the passage and the target answer, whereas in the QA task, the answer will be generated given the question and the passage. They also leverage a policy-gradient reinforcement learning algorithm to overcome exposure bias (a major problem resulted from sequence learning with cross-entropy loss function).They case both QG and QA tasks into one process by firstly matching the input passage against the query, then generating the output based on the matching results.

As for the training process, they first pretrain the model with cross-entropy loss and then they fine tune the model parameters with policy-gradient reinforcement learning to alleviate the exposure bias problem. During the policy-gradient reinforcement learning algorithm, they end up adopting a similar sampling strategy as the scheduled sampling strategy for generating the sampled output.

4.2.5.1.5 Summary

As mentioned earlier, QG and QA tasks are intrinsically bounded and one cannot find solution for either of them without taking the other party into account. In this section, we have discussed some approaches that many groups of people have taken to help machine learning both tasks simultaneously. Some exciting findings have been presented here. For our problem, it is very motivating to see these progress and learn from their approaches. In sum, the general setup is similar to dual learning framework, we need to tie QG and QA parts of the algorithms together. In the first diagram of the section, we can see that they connect the loss function from both sides of the model which is very similar to the strategy adopted by GAN (Generative adversarial network). Some advanced mechanisms are proposed as well i.e. symmetric hierarchical attention and policy-gradient reinforcement learning algorithm.

4.2.5.2 Open-ended Question

4.2.5.2.1 Problem Formulation

Open-ended questions bring clarity.

As we mentioned above, the open-ended question could be roughly split into 2 categories. One is general open-ended questions or a more specific open-ended question.

Technically specking, these 2 categories are not that particular distinct since both problems require the system to be able to draw some conclusion based on the context and question provided; the answer is allowed to have a pretty high degree of freedom. In other words, our system should be able to evaluate the answer with relatively flexible rules or standards.

Based our assumptions, we will just combine these 2 problems into 1 here to show some research findings that can possibly support our unified goal.

It may appear unapproachable at the first glance to teach a system to have answers for or even evaluate this type of problems. Or it is just an indication that we should probably reframe our issue and break it apart into smaller elements. Based on our research, we suggest thinking of this type of issue as a particular type of QA problem; the difference is that after the QA procedure, we need to match and evaluate the answers generated by machine and the learner such that we can provide an adequate feedback.

Here we would like to start with a existing knowledge evaluation system that has been used for grading the essays automatically - Automated essay scoring (AES) which focuses on automatically analyzing the quality of writing and assigning a score to the text. AES systems may rely not only on grammars, but also on more complex features such as semantics, discourse and pragmatics. It has four general types:

- Essay Grade: it is known as the first AES system.
- Intelligent Essay Assessor: it is using Latent Semantic Analysis features
- E-rater: it has been used by the ETS to score essay portion of GMAT
- IntelliMetric: it is developed and used by the College Board for placement purposes.

Enough for the introduction, let's begin reviewing our papers.

4.2.5.2.1.1 Case Studies

1. In this paper Neural Automated Essay Scoring and Coherence Modeling for Adversarially Crafted Input, they develop a network that can effectively learn connectedness features between sentences and propose a framework for integrating and jointly training the local coherence model with a state-of-art AES.

They examine the robustness of the AES model to adversarially crafted input and specifically focus on input related to local coherence; A local coherence model can evaluate the writing based on its ability to rank coherently ordered sequence of sentences higher than their counterparts.

Their models are Local Coherence (LC) model and LSTM AES model. The first model has 2 main parts: sentence representation and clique representation; and he second model is a combined model that does vector concatenation and joint learning.

2. In this paper Open-Ended Long-form Video Question Answering via Adaptive Hierarchical Reinforced Networks, they study the problem of open-ended video question answering from the viewpoint of adaptive hierarchical reinforced encoder-decoder network learning. They present the adaptive hierarchical encoder network to learn the joint representation of the long-form video contents according to the question with adaptive video segmentation. They also develop the reinforced decoder network to generate the neural language answer for open-ended video question answering. Meanwhile, they also construct a large-scale dataset for open-ended long-form video QA and validate the effectiveness of the proposed method.

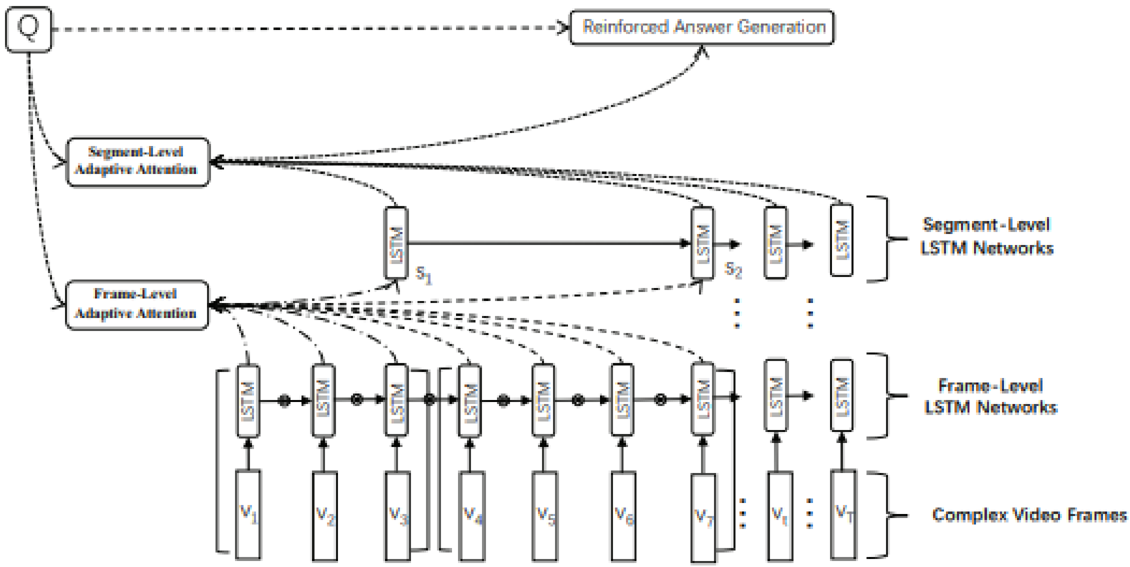


Figure 4.5: Open-Ended Long-form Video QA Network

The framework of Adaptive Hierarchical Reinforced Networks is are below:

The first part is the hierarchical encoder networks that learn the joint representation of multimodal attentional video and textual question with adaptive video segmentation.

The second part is the reinforced decoder networks that generate the natural language answers for open-ended video question answering.

3. In this paper, Multi-turn Dialogue Response Generation in an Adversarial Learning Framework, they propose an adversarial learning approach that can generate multi-turn dialogue responses. The network framework that they introduce is call *hredGAN* that is based on conditional GANs. The generator part of the model is a modified hierarchical recurrent encoder-decoder network (HRED) and the discriminator is a word-level bi-directional LSTM RNN that shares context and word embedding with the generator.

During the inference step, noise sampling is conditioned on the dialogue history and is used to perturb the generator's latent space for generating possible responses. The final response is the one ranked the best by the discriminator.

In sum, their hredGAN combines both generative and retrieval-based multi-turn dialogue systems to improve the model's performance. The underlying mechanism is that generator and the discriminator share the context and word embedding and this allows for joint end-to-end training using back-propagation.

4.2.5.2.1.2 Summary

Based on our limited research, we found that it is also achievable for our system to generate the answers for open-ended questions based on the educational video and provide appropriate feedback/rating for the learner. The first paper presents a newly developed AES model that can rate learner's writing. It also demonstrates a possible way of enhance the AES model by training it with the adversarially crafted input.

In the second paper, we discuss a network that can answer the open-ended questions based on the video and a given question. Their Adaptive Hierarchical Reinforced Networks are composed of hierarchical encoder networks and the reinforced decoder networks. With their framework, we can easily extend the research topic into educational video specifically.

Similar to the last peper, this paper shows that it is possible to generate responses conditioned on the context. By leveraging conditional GAN model framework, their model's performance is significantly improved.

4.2.6 Summary of Learning and Feedback Networks

Based on our previous discussion, we find that both QG and QA (including VQA) tasks have been well-researched. A numerous of specifically designed algorithms were presented and proved effective for solving these problems.

There are also some research has been done to tackle both QG and QA problems at the same time. The research we presented may not be particularly applicable to the video content. But the implication is clear, by combining some techniques we learned from the QG and QA sections separately with some frameworks like dual learning introduced in the dual task section, it is plausible for us to conclude that the coherent QG + QA system for our purpose is not that far-fetched.

As what we anticipated, the research is significantly less in the open-ended question realm. However, some techniques presented in our research finding session are very relevant and could certainly serve as our starting point for solving our problem such as AES model and open-ended question answering networks. As more and more research comes out, we should expect more effective solutions to come out soon.

Current research is promising but we need more research and innovation in this area.

In open-ended question section, we find that our current research cannot fully support our goal of taking in the answer in any possible formats (i.e. a short video presentation or a recording) besides writing.

4.2.6.1 Datasets and Annotation Needed

In order to approach this problem from scratch, we need to create our own dataset for which we will provide some related resources to start with:

1. YouTube-8M Dataset. This is a large-scale labeled video dataset that consists of millions of YouTube video IDs, with high-quality generated annotations from a diverse vocabulary of 3800+ visual entities. As you can see from its introduction, it comes with precomputed audio-visual features from billions of frames and audio segments. In short, we can expect the following content from this dataset:

- the dataset consists of 6.1M videos URLs, labeled with a vocabulary of 3863 visual entities
- the video-level dataset comes out to be 18 GB in size, while the frame-level features are approximately 1.3 TB
- it comes with pre-extracted audio & visual features from every second of video.

Though the video content is not limited to education category, we can still use it to get a strong baseline model.

Naturally, the next step would be constrain our model to train on particularly educational content. The data needed for training may include the raw video clip, annotation/caption of the whole video content, and audio part of the video.

2. In this study Video Captions for Online Courses: Do YouTube's Auto-generated Captions Meet Deaf Students' Needs?, they studied the auto-generated captions generated on YouTube online courses. They find that, on average, there were 7.7 phrase errors per minute of a total 68 minutes video caption. It is been said, we still need to do a lot of annotation work before we can finally compose our own training dataset.

Other resources that could possibly help us with out tasks are as below:

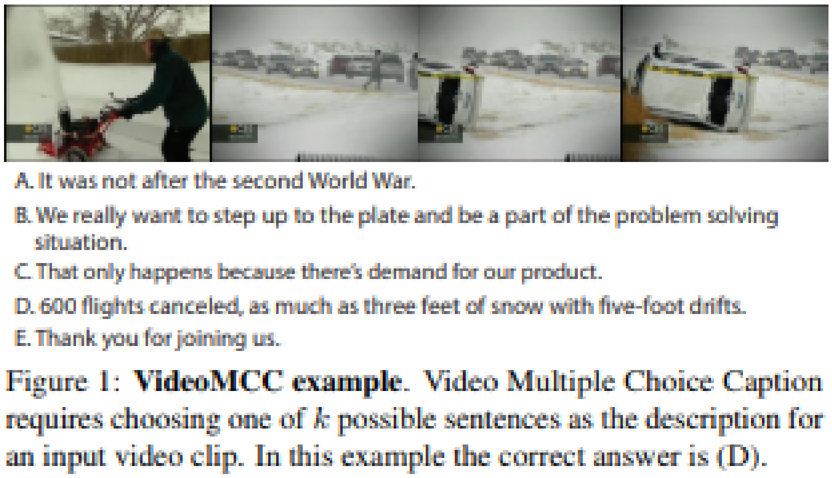


Figure 4.6: VideoMCC

3. VideoMCC. In their paper, they formulate Video Multiple Choice Caption (VideoMCC) as a way to assess video comprehension through an easy-to-interpret performance measure. In their paper VideoMCC: a New Benchmark for Video Comprehension they propose to cast video understanding in the form of multiple choice tests that assess the ability of the algorithm to comprehend the semantics of the video. Example is as below:

4. As what we have covered earlier, this paper MovieQA: Understanding Stories in Movies through Question-Answering, they introduced a new dataset called MovieQA dataset that can evaluate automatic story comprehension from both video and text.

Here are 2 figures that can help you better understand their dataset:

5. In this paper Video Description: A Survey of Methods, Datasets and Evaluation Metrics multiple methods, datasets and evaluation metrics for video description task in a comprehensive survey.

6. Inspired by this paper QuAC : Question Answering in Context in which they present QuAC dataset for QA in Context that contains 14K information-seeking QA dialogs such as a student who poses a sequence of freeform question to learn as much as possible about a hidden Wikipedia text or a teacher who answers the questions by providing short excerpts from the text, we are convinced that it is might also be possible to develop a system that can allow student to pause the video and ask our system a information-seeking question and then get the answer from our system based on the current content. .

4.3 Knowledge Graph [DRAFT]

Next, we need to consider how we can select an adequate and relevant learning material and generate an effective learning map for the learners based on their current progress and the general knowledge graph/map, given the ever growing amount of educational content on the web.

As I mentioned earlier, learning is a knowledge accumulation process. Knowledge itself has its unique structure that can help us learn in a most effective and productive way. Knowledge Graph is a great tool that we developed to map and present the structure of knowledge. In shirt, knowledge graphs are collections of relational facts, where each fact states that a certain relation holds between 2 entities.

Now we will consider the knowledge graph as the backbone.

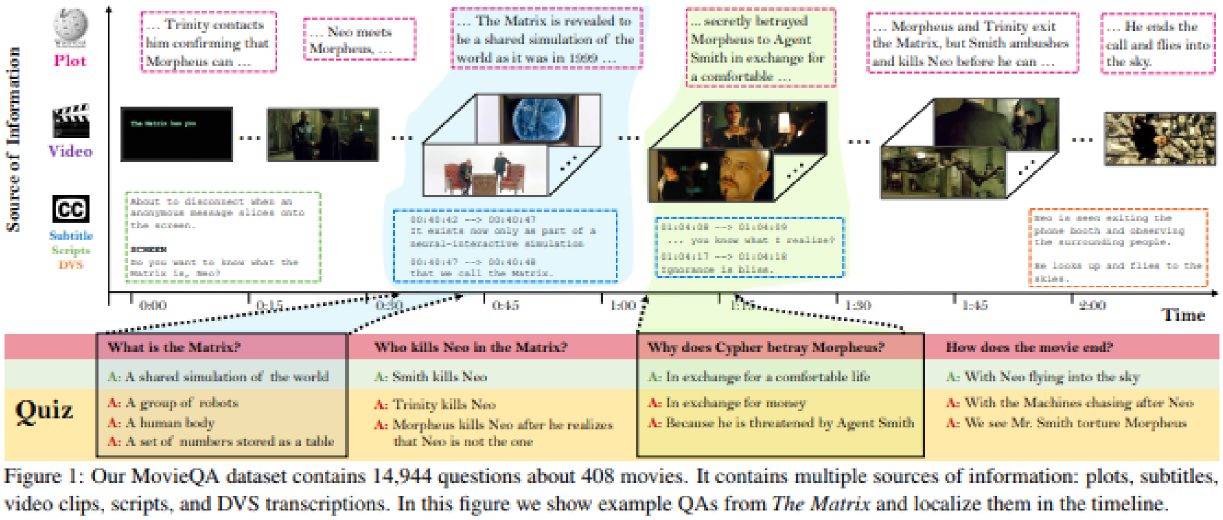


Figure 4.7: MovieQA_1

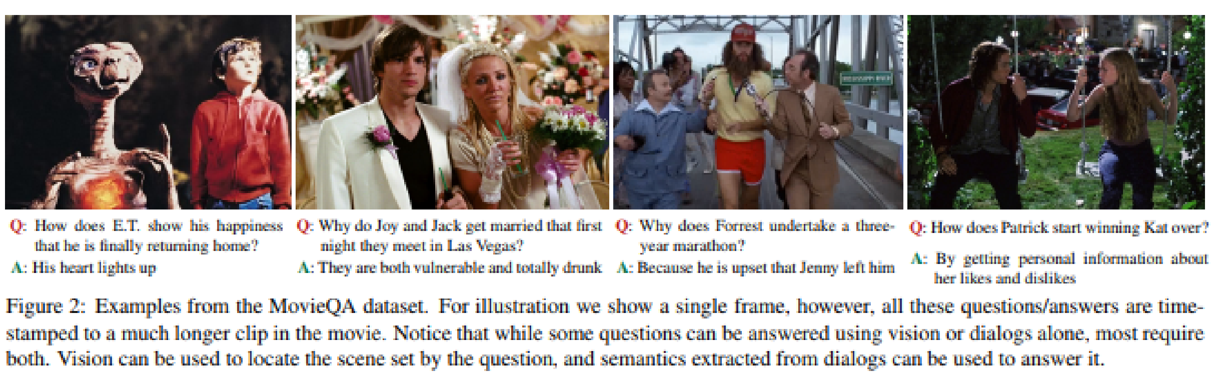


Figure 4.8: MovieQA_2

4.3.1 What is a graph?

> Graphs are networks of dots and lines - Graph Theory (Dover Books)

Mathematically speaking, graphs are mathematical structures used to model pairwise relations between objects. A graph in this context is made of vertices, nodes, or points which are connected by edges, arcs or lines. Typically a graph consists of two sets. A set of vertexes and a set of edges

$$GRAPH_{v,e} = \begin{pmatrix} v_{1,1} & a_{1,2} & \cdots & a_{1,n} \\ e_{2,1} & e_{2,2} & \cdots & e_{2,n} \end{pmatrix}$$

As for the knowledge graph, it is a knowledge base. Often when people talk about knowledge graph, they are referring to the multi-relational graph used by Google and its services to enhance search engine's results with information gathered from a variety of sources. Per Wikipedia, Google's Knowledge Graph uses a graph database to provide structured and detailed information about the topic in addition to a list of links to other sites.

In general, a knowledge graph represents a knowledge domain. It connects things of different types in a systematic way. Knowledge graphs encode knowledge arranged in a network of nodes and links rather than tables and columns. With knowledge graphs, people and machines can benefit from a dynamically growing semantic network of facts about things. In other words, we can use it to capture the facts related to people, processes, applications, data and many other custom objects as well as their relationships among them.

If you want, they can also capture evidence that can be used to attribute the strengths of these relationships.

Also, we have found a lot of applications that demonstrate that existing generic knowledge graphs have shown advantages to support semantic search(i.e. Google's Knowledge Graph), personal assistant(i.e. Apple's Siri) and deep question answering (i.e. Wolfram Alpha and IBM's Watson).

4.3.2 Problem Formulation

Given we've implemented the learning and feedback module, knowing where a given piece of education content fits into the knowledge space is a vital task if we want the knowledge footprint to make a learner predictable to others as well as being able to recommend new educational content that the learner can take on successfully. We will need the following things to connect educational content.

> A classifier to take a piece of educational content

A graph dedicated to education should do the following:

- Provide flexibility to add new subjects
- Connect related subjects to each
- Map concepts with the subject
- Connect concepts related to the content

4.3.3 Automatic Knowledge Graph Construction

Classic knowledge representation techniques allow a knowledge engineer o create rules that can be interpreted by a reasoner to infer new or missing triples(subject, predicate, object). These rules are usually expressed through an ontology which allows for the propagation of properties from top classes to the lower classes.

However, we are looking for solutions that can allow us to complete our educational knowledge graph building process. Based on our research, generic knowledge graphs usually cannot sufficiently support many domain-specific applications i.e. education and finding the representation of the graph to feed the triples into a

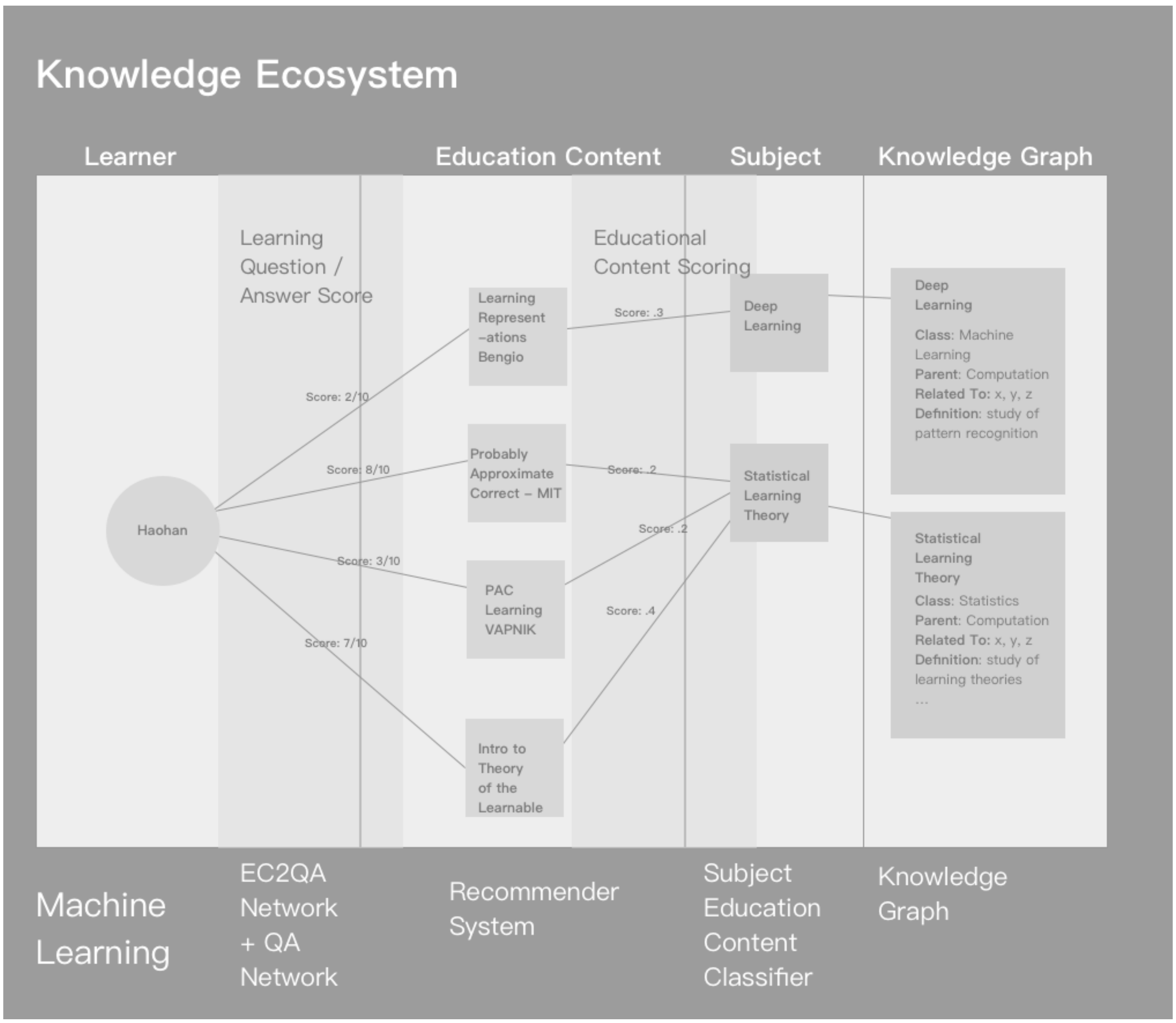


Figure 4.9: Knowledge Ecosystem

machine learning or deep learning algorithm is still an open area of research. As a start, let's focus on how to automate the eduction knowledge graph construction process.

There have been several papers that provide promising results to the automation of constructing a knowledge graph. Let's take a look.

4.3.4 Case Studies

1. In this paper KnowEdu: A System to Construct Knowledge Graph for Education, they propose a system KnowEdu that can automatically construct knowledge graph for education. In short, the system is able to extract concepts of subjects or courses and then identifies the educational relations between the concepts.

More importantly, it adopts the neural sequence labeling algorithm on pedagogical data to extract instruction concepts and employs probabilistic association rule mining on learning assessment data to identify the significance of the relations.

In sum, their system consists of the following modules:

- Instructional Concept Extraction Module to extract instructional concepts for a given subject or course.
- Educational Relation Identification Module to identify the educational relations that interlink instructional concepts to assist the learning and teaching process directly.

Below is a block diagram of KnowEdu System.

They used conditional random field (CRF) model for entity or terminology recognition task. Moreover, they adopt neural network, or more particularly Gated recurrent unit network (GRU) architecture for neural sequence labeling on educational entity extraction task.

In terms of relation identification they implement probabilistic association data mining techniques on learning assessment adata and accomplish the task of educational relation identification.

A snapshot of the knowledge graph for mathematics generated by knowedu system.

Below are some approaches related to knowledge graph (KG) embedding which is used to embed components of a KG including entities and relations into continuous vector space so as to simply the manipulation while preserving the inherent structure of a KG.

As for its benefits and importance for our task, it can help with a variety of downstream tasks i.e. KG completion and relation extraction, and hence be used to drastically improve the information acquisition speed for KG.

2. In this paper Generalized Embedding Model for Knowledge Graph Mining, they have presented a model for learning neural presentation of generalized knowledge graphs using a novel multi-shot unsupervised neural network model, called the **Graph Embedding Network (GEN)**. This model is able to learn different types of knowlege graphs from a universal perspective and it provides flexibility in learning representations that work on graphs conforming to different domains.

In developing their model, they extend the traditional one-shot supervised learning mechanism by introducing a multi-shot unsupervised learning framework where a 2-layer MLP network for every shot. This framework can in turn be used to accommodate both homogeneous and heterogeneous networks.

3. In this paper Probabilistic Knowledge Graph Embeddings, they explored a new type of embedding model that can link prediction in relational knowledge graph. They start from a problem that even large knowledge graphs typically contain only few facts per entity, leading effectively to a small data problem where parameter uncertainty matters. As for the solution, they suggest that the knowledge graphs should be treated within a Bayesian framework.

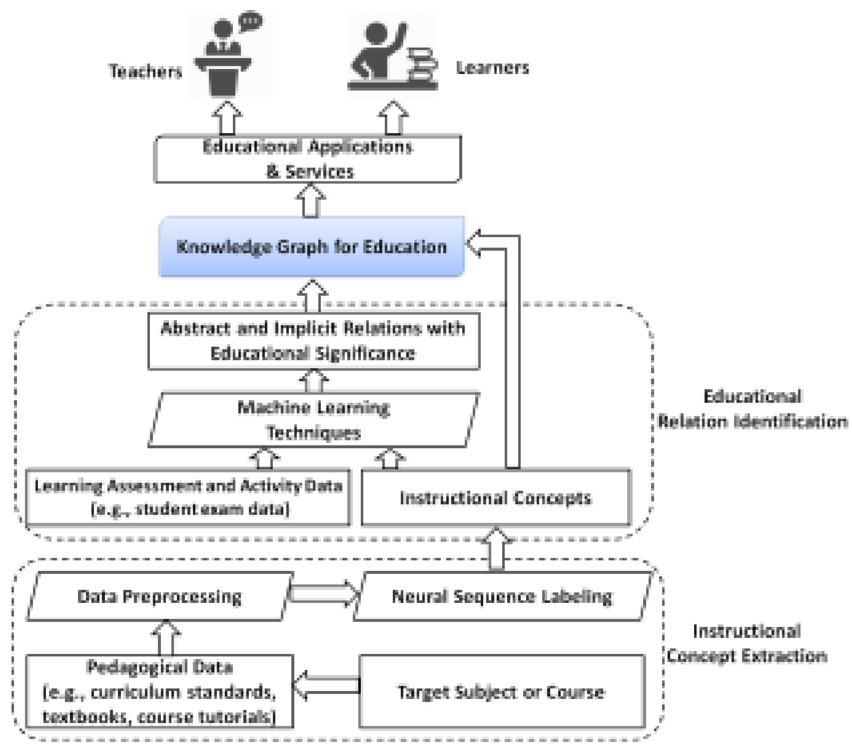


FIGURE 1. **Block Diagram of the KnowEdu System.**

Figure 4.10: knowedu

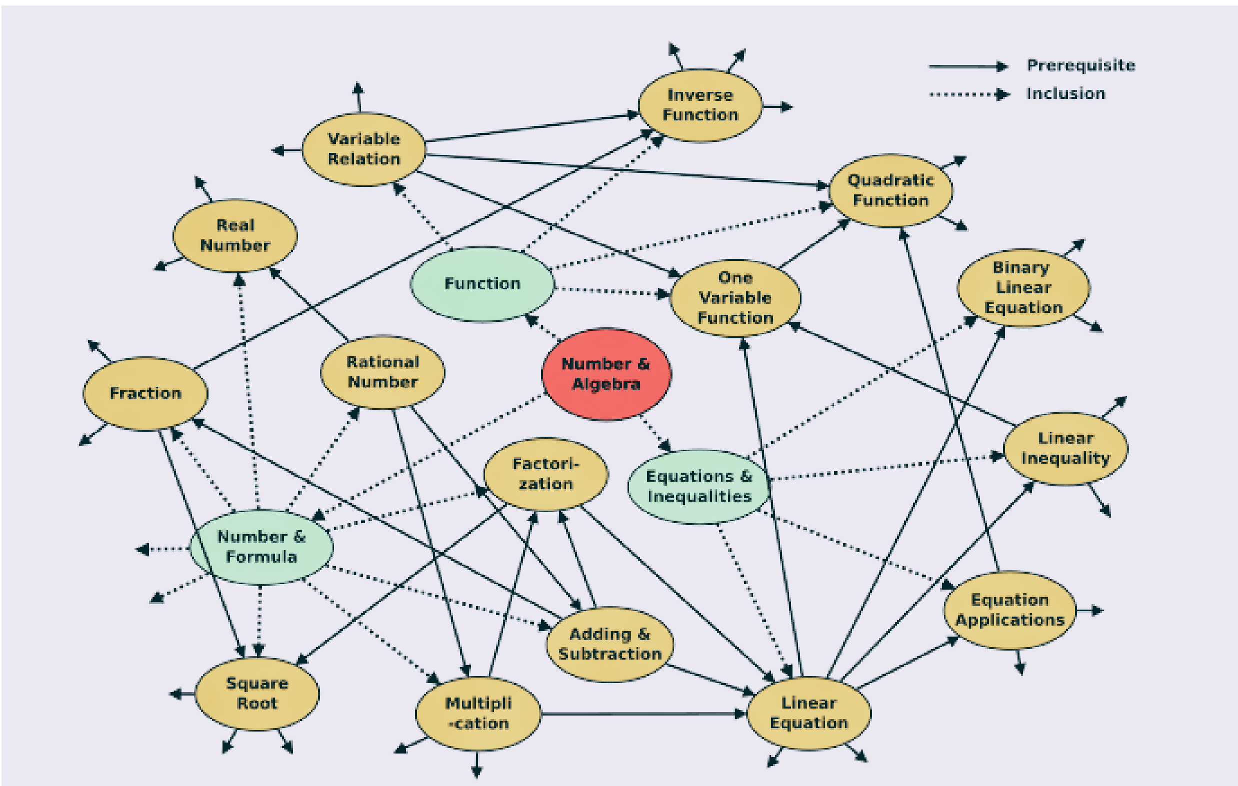


FIGURE 6. A snapshot of built knowledge graph for mathematics.

Figure 4.11: knowledge_graph

In short, they present a probabilistic interpretation of existing knowledge graph embedding models. By reformulating the models like ComplEx and DistMult, they construct the generative models for relational facts.

They also apply stochastic variational inference to estimate an approximate posterior for each entity and relation embedding in the knowledge graph. By doing so, they can estimate the uncertainty, but more importantly, they can use gradient-based hyperparameter optimization by stochastic gradient descent on the optimized variational bound.

As a result, their model shows experimentally new state-of-art results in link prediction task.

4.3.5 Summary of Knowledge Graph

Based on our research, we are very pleased to see some great progress has been made on bridging the KG automation process with deep learning and other machine learning techniques.

As what we discussed above, the first paper introduces a system that almost exactly matches our goal. The carefully walk us through the current progress and possible solutions for solving each obstacles in developing such a educational knowledge graph. For the instructional concept extraction task, they use both CRF model and neural sequence labeling algorithm to achieve a high performance. They employ probabilistic association rule mining on learning assessment data to identify the relations with educational significance.

The last 2 papers demonstrate the progress that has been made in KG embedding learning domain. As mentioned above, as one of the most effective methods in representing knowledge graphs. The development of this field may offer some great implication for the future KG automation and acquisition work/research.

4.3.5.1 Key Components

Here are some key components that we found important of building an automated knowledge graph for education:

1. Entity recognition that aims to extract concept of interest from structured or unstructured data.
2. Relation identification that leverages on the semantic meaning of data.

4.3.5.2 Possible Next Steps

Here are some of our research summary regarding the steps of creating such an educational knowledge graph:

1. In terms of entity recognition task, We need to first get the data from some reliable open semantic sources i.e. Wikipedia or Freebase. Or we can crawl the data online on our own to find high quality training data. In the next section we will be listing out some resources that might help.
2. Next, we need to create the model to map the relation among the entities. There are plenty of great github that we can use to help us with this task. Or we can use some tools developed for this purpose i.e. node.js and Wolfram Mathematica embedded symbolic functions or just TensorFlow. The typically techniques we will employ are NLP and semantic data tagging or labeling techniques.
3. Naturally, after the entity extraction and relationship mapping we will visualize our map.

4.3.5.3 Datasets and Annotaters needed

1. Knowledge Vault: A web-scale approach to probabilistic knowledge fusion. In this paper Knowledge Vault: A Web-Scale Approach to Probabilistic Knowledge Fusion, they introduce Knowledge Vault that combines extraction from Web content (obtained through analysis of text, tabular data, page structure, and human annotation) with prior knowledge derived from existing knowledge repositories.

They employ a supervised machine learning models for fusing these distinct information sources. As a result, their system can automatically construct a web-scale probabilistic knowledge base.

2. Google Knowledge graph Search API.

Below are some resources that might be helpful for starting such a job from scratch:

3. Understand how structured data works by Google.
4. Wikipedia
5. Freebase

4.4 Knowledge Journeys

The collective knowledge graph is our 'ground truth' that can be used to serve every learner in the ecosystem and be applied universally to some extent, but everyone's learning journey is still highly custom. Everyone seems to have their unique set of problems that they are curious about and they will end up taking on their own missions towards the mastery. As a result, their knowledge journeys will have a lot degree of freedom depends on their learning history, interests and who they are related to.

We cannot possibly put such an online educational ecosystem into use without taking this crucial factor into our account.

Let's first formulate our problem. Below are few key components of such a task:

1. First, we need to have a system that can match all the content that a learner has acquired with the collective educational knowledge graph;
2. Generate their personal knowledge graph with the timestamps on each content and the subject(s) it belongs to;
3. Unfold the timestamps and map the previous generated static knowledge graph onto a timeline that can display a learner's knowledge as a personal knowledge acquisition storyline/gallery;
4. Adaptively update the journey along with a learner's learning progress.

As the outcome, a learner's knowledge journey will be available anytime for the learner to review the content that he/she has learned at any past moment and for others to look into the details of one's journey.

4.5 Knowledge Footprint

Just a quick review of this concept we introduced earlier, knowledge footprint is going to be presented as a badge or a symbol to represent someone's knowledge state at a fix point in time. In a sense, this thumbnail view of a learner's knowledge will evolve and change when a learner continues his/her learning journey. By constructing such symbol(s), a learn can easily understand their current knowledge states relatively to their past and others and timely make an adjustment to alter their future learning plan.

In terms of the techniques that can be applied for this task, we would primarily consider unsupervised learning and dimensionality reduction algorithms to help us uncover and represent the visible and invisible dimensions of a learner's knowledge journey and state. Also, we believe it is going to be a teamwork that requires people like machine learning and deep learning researchers, educators, and designers to work collaboratively to ensure the optimal outcome.

Note that we will not discuss the detailed research findings or implementation steps of the last 2 elements in this essay. We will leave these areas for our future research.

4.5.1 Possible Next Step

As a reasonable next step, we would also like our system to be as personalized as possible so as to provide guidance for a learner along their knowledge journey, given that our system has already encoded and possessed the information of a learner's footprint and journey.

In this case, a recommender system might be a desirable choice for handling such a job since it is an intuitive line of defense against consumer over-choice given the ever growing educational content available on the web.

Chapter 5

Next Steps

5.1 Overview

We have now proposed one approach to better represent a modern individual's knowledge by taking the world of unstructured educational content (Youtube videos, Medium articles, etc), classifying it by it's concepts which belong to one or more subjects from a education-based knowledge graph. We've introduced learning and feedback by testing a learner's knowledge by generating a set of questions and answers conditioned on an educational content without the need for the educator to include questions and answers.

We surveyed some of the relevant machine and deep learning research, proposed the Educational Content to Questions and Answers (EC2QA) network, a novel neural network for taking in any type of educational content and generating a set of questions, answers, and evaluation of a learner's knowledge understanding.

We then proposed to tie these components together as an adaptive knowledge ecosystem consisting of an individual's knowledge footprint, mapped to a central knowledge graph, visualised over time as a learner's knowledge journey. This would serve to enable the independent (aspiring or current) learner to pursue their life-long self-study. It would take into consideration the education they acquired from unstructured sources, thereby formalising their informal knowledge for themselves and others.

5.2 Challenges

There will be many challenges in coming up with solutions to enable knowledge acquisition and representation at the learner and group level. We will address some of the primary challenges to designing the components of the proposed knowledge ecosystem:

- Datasets – EC2QA dataset – Knowledge graph dataset
- Deep Learning Architecture – EC2QA network

For our purposes we will focus on the EC2QA network and dataset as the main focus for our next steps.

5.3 EC2QA dataset

The success of deep learning techniques are predicated on the assumption that one needs a significant amount of data to train a large neural network to learn the representation that captures the set of admissible functions needed to learn a given set of concepts.

The EC2QA network will also face the same challenges it requires a large dataset of educational content (i.e. Youtube videos, Wikipedia pages or Medium articles) along with a set of questions, which will have a set of correct and incorrect answers for each question.

$$\{content1 : \{question1 : \{answer1, answer2, ...\}, question2 : \{answer1, answer2, ...\}, ...\}, ...$$

Educational Content	Concepts
Robert Sapolsky Human Behavioral Biology Lecture 1: [[[0,23,435......]]]	neurobiology, neurological disease, gene, nature v

There are many approaches to decreasing the amount of data needed while still learning a good representation of the set of concepts the architecture needs to learn. We will present an approach that we believe best utilises the intrinsic structure of educational content and using the minimal amount of data.

1. The network can be trained on unstructured educational content without questions or answers to create an *education embedding* by leveraging unsupervised techniques like variational auto-encoder (VAE). This requires a dataset of educational content, possibly many media types(audio/video/text). This could also be done by using a semi-supervised technique by supervising the media type and learning representations for the types of educational content.
2. The network can then be trained on **existing** educational content that *already* has preexisting questions and answers for specific parts of the content (i.e. Khan Academy, Udacity, Coursera). The domain of structured educational content is surely very different from the unstructured content and may hinder the network but we believe it might be the case that it helps more than it hinders but we cannot guarantee this so it is worth experimenting.
3. The final step is annotating a set of unstructured educational content with questions and answers.

5.4 Education Partners

The second step above requires a large amount of existing educational content paired with existing questions and answers. This data is rich and informative; it could help us learn an early representation and use less of our original dataset (#3) for learning such a representations. Most of these datasets have been created by experts and educators and their efforts could be valuable for our model to learn from. For this purpose, we would need to partner with large (in terms of library of content) educational institutions (i.e. Udacity, Coursera, MOOCs, Edx, Khan Academy) to work with their datasets for pretraining and collaborate on how we annotate the space of unstructured educational content.

5.5 Educator Enrichment

The third and final dataset that would be used as our primary data source to train and test the model's performance, remains the most important component as well as being the most time and labour intensive. Partnering with educators and subject matter experts to source the subspace of unstructured educational content and to create questions and answers, we would eventually arrive at a curated dataset that our model would be primarily trained on. The end result would be a new benchmark that other researchers can begin to build newer architectures to make progress on the problem domain.

5.6 Minimum Viable Dataset (Benchmark)

We propose to narrow the problem space and jumpstart research in this area by focusing on only one subject (i.e. psychology, mathematics, or design) rather than to try to take on mapping the whole space of unstructured educational content. This drastically reduces the data that is needed and the number of experts and partners needed to kickstart the initiative.

5.7 Call for collaborators

We hope to bring together collaborators that would include machine learning researchers, educators, technologists, and designers to begin our first foray into a modern knowledge ecosystem. Specifically starting with the EC2QA dataset and network, one education subject, and an educational partner.

Please email us at two@dyadxmachina.com with the subject *Knowledge Graph Initiative* or leave your email below.

We are looking for educators, researchers, and designers to collaborate. Send us your email to stay updated

Email Address *

5.8 Conclusion

In conclusion, we presented a new perspective on knowledge acquisition and representation, and proposed an ecosystem that would support a modern and adoptive knowledge ecosystem that a learner can use and rely on through their entire educational life-time.

Our main task was to take an individual and begin to get a true depiction of their knowledge beyond their traditional degree, which is only a small percentage of someone's education.

We focused on taking the world of unstructured educational content online, and how to provide structure in the form of testing and mapping it to a knowledge graph.

There is still much more research to be done in bringing to life the Educational Content to Questions and Answers (EC2QA) neural networks as well as the data needed for training and the collaboration required amongst machine learning researchers, teachers, and designers,

As deep learning researchers, we are looking forward to designing or seeing others design the minimum viable dataset, benchmark, and architecture motivated by this work.

Chapter 6

About the Authors

Independent deep learning researchers focused on using machine learning for the good of humanity and beyond.

6.1 Haohan Wang

LinkedIn ## Fanli Zheng (Christian Ramsey) LinkedIn ## Contact Feel Free to contact us if you have any question:

Visit our website dyad x machina

Haohan Wang: haohan723@gmail.com

Fanli Zheng (Christian): thechristianramsey@gmail.com

Bibliography