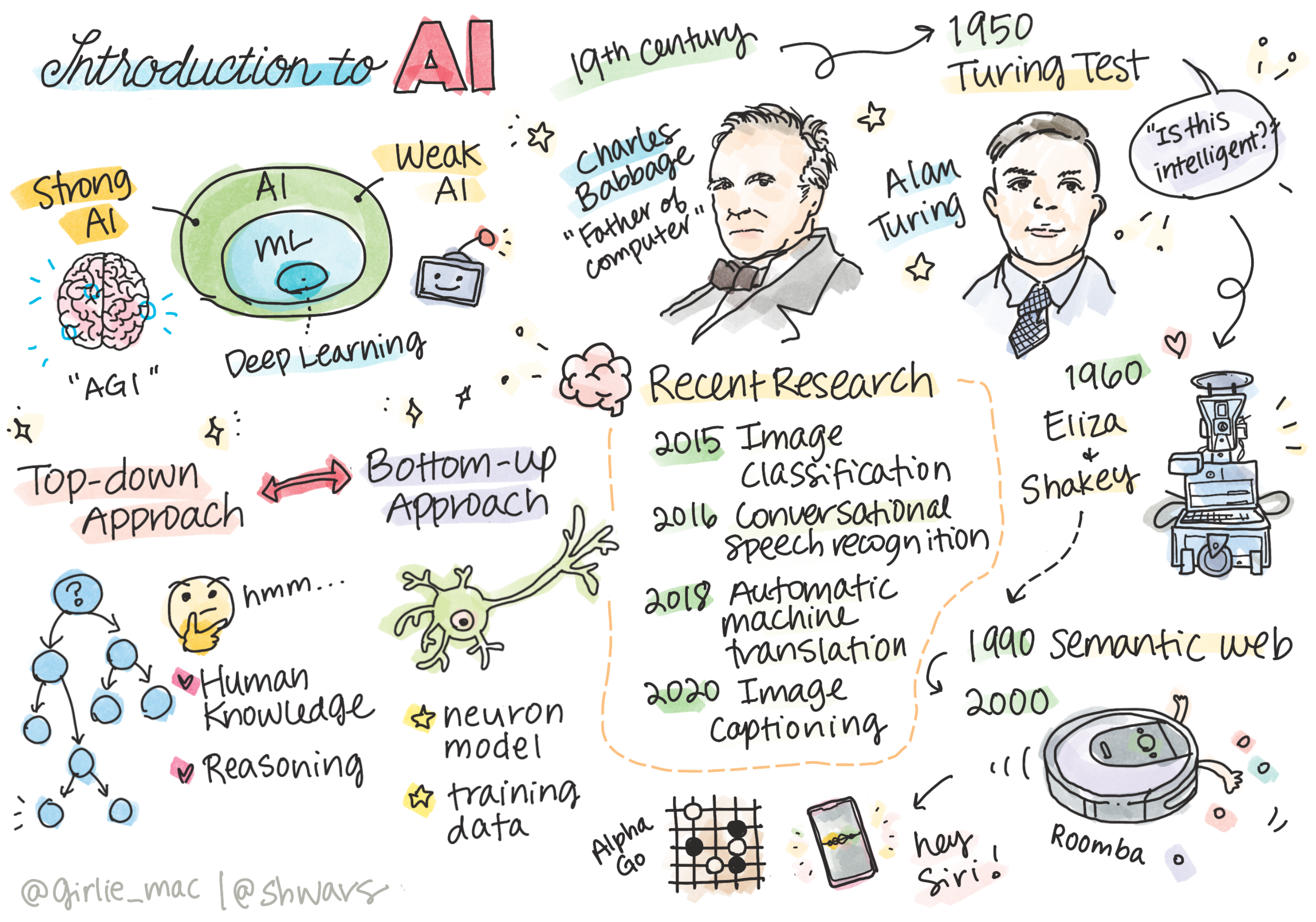
# Introduction to AI

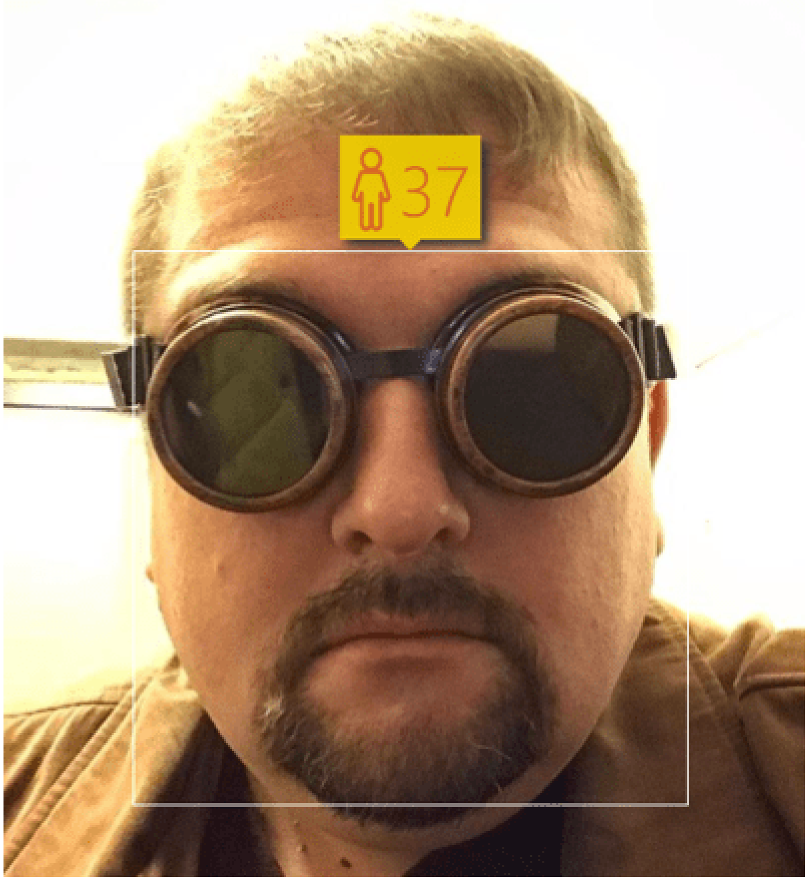


> Sketchnote by Tomomi Imura

## Pre-lecture quiz

**Artificial Intelligence** is an exciting scientific discipline that studies how we can make computers exhibit intelligent behavior, e.g. do those things that human beings are good at doing.

Originally, computers were invented by Charles Babbage to operate on numbers following a well-defined procedure - an algorithm. Modern computers, even though significantly more advanced than the original model proposed in the 19th century, still follow the same idea of controlled computations. Thus it is possible to program a computer to do something if we know the exact sequence of steps that we need to do in order to achieve the goal.



> Photo by Vickie Soshnikova

> ✅ Defining the age of a person from his or her photograph is a task that cannot be explicitly programmed, because we do not know how we come up with a number inside our head when we do it.

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There are some tasks, however, that we do not explicitly know how to solve. Consider determining the age of a person from his/her photograph. We somehow learn to do it, because we have seen many examples of people of different age, but we cannot explicitly explain how we do it, nor can we program the computer to do it. This is exactly the kind of task that are of interest to **Artificial Intelligence** (AI for short).

✅ Think of some tasks that you could offload to a computer that would benefit from AI. Consider the fields of finance, medicine, and the arts - how are these fields benefiting today from AI?

## Weak AI vs. Strong AI

The task of solving a specific human-like problem, such as determining a person's age from a photo, can be called **Weak AI**, because we are creating a system for only one task, and not a system that can solve many tasks, such as can be done by a human being. Of course, developing a generally intelligent computer system is also extremely interesting from many points of view, including for students of the philosophy of consciousness. Such system would be called **Strong AI**, or **Artificial General Intelligence** (AGI).

## The Definition of Intelligence and the Turing Test

One of the problems when dealing with the term **Intelligence** is that there is no clear definition of this term. One can argue that intelligence is connected to **abstract thinking**, or to **self-awareness**, but we cannot properly define it.

> Photo by Amber Kipp from Unsplash

To see the ambiguity of a term *intelligence*, try answering a question: "Is a cat intelligent?". Different people tend to give different answers to this question, as there is no universally accepted test to prove the assertion true or not. And if you think there is - try running your cat through an IQ test...

✅ Think for a minute about how you define intelligence. Is a crow who can solve a maze and get at some food intelligent? Is a child intelligent?

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When speaking about AGI we need to have some way to tell if we have created a truly intelligent system. Alan Turing proposed a way called a **Turing Test**, which also acts like a definition of intelligence. The test compares a given system to something inherently intelligent - a real human being, and because any automatic comparison can be bypassed by a computer program, we use a human interrogator. So, if a human being is unable to distinguish between a real person and a computer system in text-based dialogue - the system is considered intelligent.

> A chat-bot called Eugene Goostman, developed in St.Petersburg, came close to passing the Turing test in 2014 by using a clever personality trick. It announced up front that it was a 13-year old Ukrainian boy, which would explain the lack of knowledge and some discrepancies in the text. The bot convinced 30% of the judges that it was human after a 5 minute dialogue, a metric that Turing believed a machine would be able to pass by 2000. However, one should understand that this does not indicate that we have created an intelligent system, or that a computer system has fooled the human interrogator - the system didn't fool the humans, but rather the bot creators did!

✅ Have you ever been fooled by a chat bot into thinking that you are speaking to a human? How did it convince you?

## Different Approaches to AI

If we want a computer to behave like a human, we need somehow to model inside a computer our way of thinking. Consequently, we need to try to understand what makes a human being intelligent.

> To be able to program intelligence into a machine, we need to understand how our own processes of making decisions work. If you do a little self-introspection, you will realize that there are some processes that happen subconsciously – eg. we can distinguish a cat from a dog without thinking about it - while some others involve reasoning.

There are two possible approaches to this problem:

| Top-down Approach (Symbolic Reasoning) | Bottom-up Approach (Neural Networks) |
|---|---|
| A top-down approach models the way a person reasons to solve a problem. It involves extracting **knowledge** from a human being, and representing it in a computer-readable form. We also need to develop a way to model **reasoning** inside a computer. | A bottom-up approach models the structure of a human brain, consisting of huge number of simple units called **neurons**. Each neuron acts like a weighted average of its inputs, and we can train a network of neurons to solve useful problems by providing **training data**. |

There are also some other possible approaches to intelligence:

- An **Emergent**, **Synergetic** or **multi-agent approach** are based on the fact that complex intelligent behaviour can be obtained by an interaction of a large number of simple agents. According to evolutionary cybernetics, intelligence can *emerge* from more simple, reactive behaviour in the process of *metasystem transition*.
- An **Evolutionary approach**, or **genetic algorithm** is an optimization process based on the principles of evolution.

We will consider those approaches later in the course, but right now we will focus on two main directions: top-down and bottom-up.

## The Top-Down Approach

In a **top-down approach**, we try to model our reasoning. Because we can follow our thoughts when we reason, we can try to formalize this process and program it inside the computer. This is called **symbolic reasoning**.

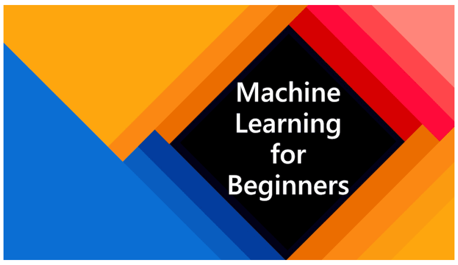
People tend to have some rules in their head that guide their decision making processes. For example, when a doctor is diagnosing a patient, he or she may realize that a person has a fever, and thus there might be some inflammation going on inside the body. By applying a large set of rules to a specific problem a doctor may be able to come up with the final diagnosis.

This approach relies heavily on **knowledge representation** and **reasoning**. Extracting knowledge from a human expert might be the most difficult part, because a doctor in many cases would not know exactly why he or she is coming up with a particular diagnosis. Sometimes the solution just comes up in his or her head without explicit thinking. Some tasks, such as determining the age of a person from a photograph, cannot be at all reduced to manipulating knowledge.

## Bottom-Up Approach

Alternately, we can try to model the simplest elements inside our brain – a neuron. We can construct a so-called **artificial neural network** inside a computer, and then try to teach it to solve problems by giving it examples. This process is similar to how a newborn child learns about his or her surroundings by making observations.

✅ Do a little research on how babies learn. What are the basic elements of a baby's brain?

> **What about ML?**
>
> | | |
> |---|---|
> | Part of Artificial Intelligence that is based on computer learning to solve a problem based on some data is called **Machine Learning**. We will not consider classical machine learning in this course - we refer you to a separate Machine Learning for Beginners curriculum. |  |

## A Brief History of AI

Artificial Intelligence was started as a field in the middle of the twentieth century. Initially symbolic reasoning was a prevalent approach, and it led to a number of important successes, such as expert systems – computer programs that were able to act as an expert in some limited problem domain. However, it soon became clear that such approach does not scale well. Extracting the knowledge from an expert, representing it in a computer, and keeping that knowledgebase accurate turns out to be a very complex task, and too expensive to be practical in many cases. This led to so-called AI Winter in the 1970s.

Brief History of AI

> Image by Dmitry Soshnikov

As time passed, computing resources became cheaper, and more data has become available, so neural network approaches started demonstrating great performance in competing with human beings in many areas, such as computer vision or speech understanding. In the last decade, the term

Artificial Intelligence has been mostly used as a synonym for Neural Networks, because most of the AI successes that we hear about are based on them.

We can observe how the approaches changed, for example, in creating a chess playing computer program:

- Early chess programs were based on search – a program explicitly tried to estimate possible moves of an opponent for a given number of next moves, and selected an optimal move based on the optimal position that can be achieved in a few moves. It led to the development of the so-called alpha-beta pruning search algorithm.
- Search strategies work well towards the end of the game, where the search space is limited by a small number of possible moves. However, in the beginning of the game the search space is huge, and the algorithm can be improved by learning from existing matches between human players. Subsequent experiments employed so-called case-based reasoning, where the program looked for cases in the knowledge base very similar to the current position in the game.
- Modern programs that win over human players are based on neural networks and reinforcement learning, where the programs learn to play solely by playing a long time against itself and learning from its own mistakes – much like human beings do when learning to play chess. However, a computer program can play many more games in much less time, and thus can learn much faster.

✅ Do a little research on other games that have been played by AI.

Similarly, we can see how the approach towards creating “talking programs” (that might pass the Turing test) changed:

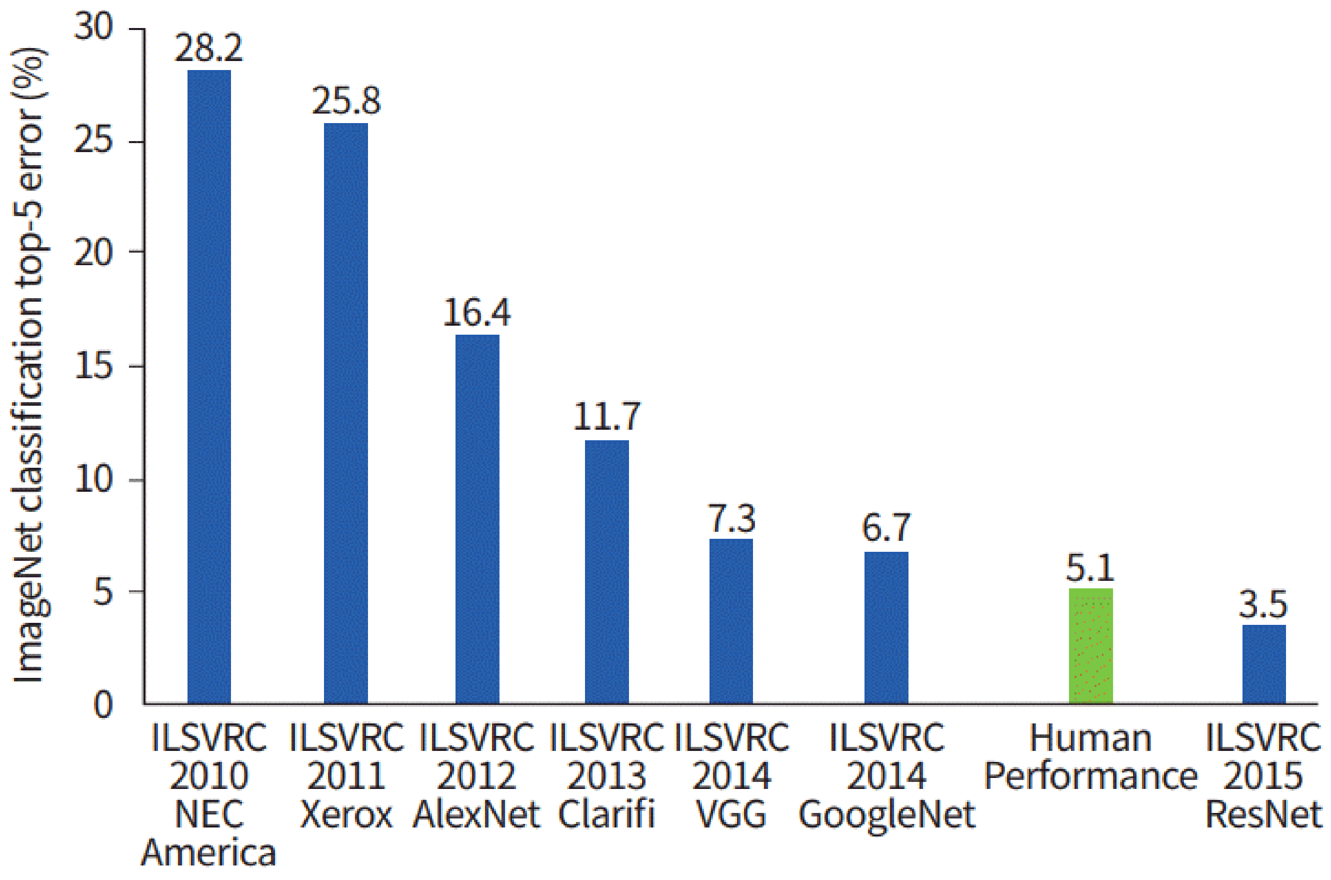
- Early programs of this kind such as Eliza, were based on very simple grammatical rules and the re-formulation of the input sentence into a question.
- Modern assistants, such as Cortana, Siri or Google Assistant are all hybrid systems that use Neural networks to convert speech into text and to recognize our intent, and then employ some reasoning or explicit algorithms to perform required actions.
- In the future, we may expect complete neural-based model to handle dialogue by itself. The recent GPT and Turing-NLG family of neural networks show great success in this.

the Turing test's evolution

> Image by Dmitry Soshnikov, photo by Marina Abrosimova, Unsplash

## Recent AI Research

The huge recent growth in neural network research started around 2010, when large public datasets started to become available. A huge collection of images called ImageNet, which contains around 14 million annotated images, gave birth to the ImageNet Large Scale Visual Recognition Challenge.



> Image by Dmitry Soshnikov

In 2012, Convolutional Neural Networks were first used in image classification, which led to a significant drop in classification errors (from almost 30% to 16.4%). In 2015, ResNet architecture from Microsoft Research achieved human-level accuracy.

Since then, Neural Networks demonstrated very successful behaviour in many tasks:

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| Year | Human Parity achieved |
|---|---|
| 2015 | Image Classification |
| 2016 | Conversational Speech Recognition |

| Year | Human Parity achieved |
|---|---|
| 2018 | Automatic Machine Translation (Chinese-to-English) |
| 2020 | Image Captioning |

Over the past few years we have witnessed huge successes with large language models, such as BERT and GPT-3. This happen happened mostly due to the fact that there is a lot of general text data available that allows us to train models to capture the structure and meaning of texts, pre-train them on general text collections, and then specialize those models for more specific tasks. We will learn more about Natural Language Processing later in this course.

## 🚀 Challenge

Do a tour of the internet to determine where, in your opinion, AI is most effectively used. Is it in a Mapping app, or some speech-to-text service or a video game? Research how the system was built.

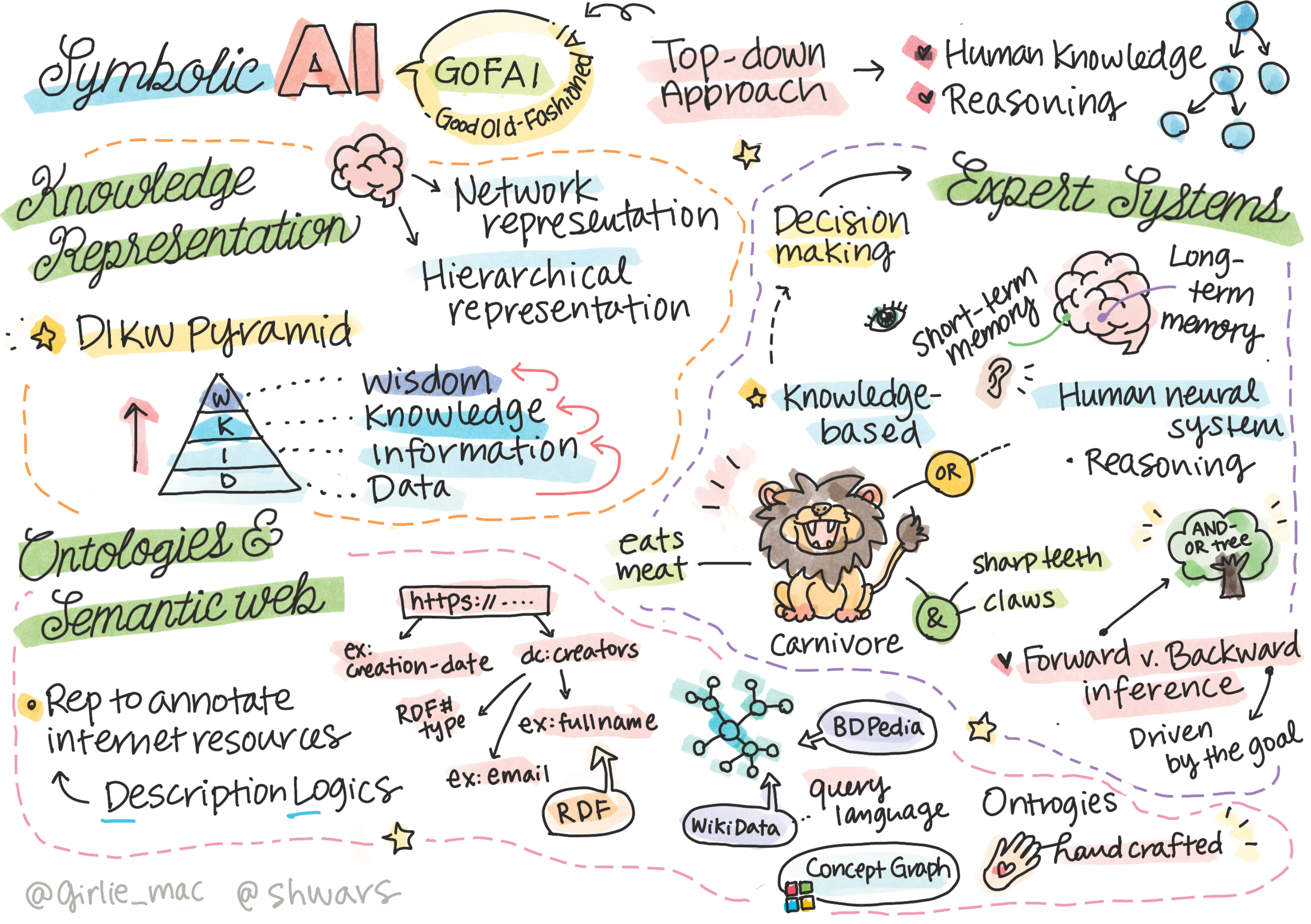
## Post-lecture quiz

## Review & Self Study

Review the history of AI and ML by reading through this lesson. Take an element from the sketchnote at the top of that lesson or this one and research it in more depth to understand the cultural context informing its evolution.

**Assignment**: Game Jam

# Knowledge Representation and Expert Systems



Sketchnote by [Tomomi Imura](#)

The quest for artificial intelligence is based on a search for knowledge, to make sense of the world similar to how humans do. But how can you go about doing this?

## [Pre-lecture quiz](#)

In the early days of AI, the top-down approach to creating intelligent systems (discussed in the previous lesson) was popular. The idea was to extract the knowledge from people into some machine-readable form, and then use it to automatically solve problems. This approach was based on two big ideas:

- Knowledge Representation
- Reasoning

## Knowledge Representation

One of the important concepts in Symbolic AI is **knowledge**. It is important to differentiate knowledge from *information* or *data*. For example, one can say that books contain knowledge, because one can study books and become an expert. However, what books contain is actually called *data*, and by reading books and integrating this data into our world model we convert this data to knowledge.

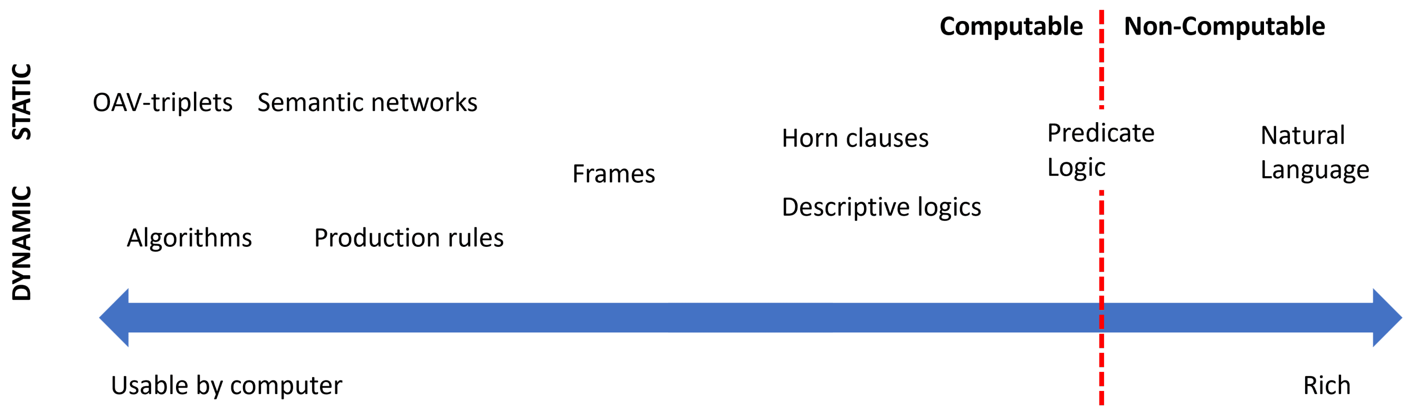
> ✅ **Knowledge** is something which is contained in our head and represents our understanding of the world. It is obtained by an active **learning** process, which integrates pieces of information that we receive into our active model of the world.

Most often, we do not strictly define knowledge, but we align it with other related concepts using DIKW Pyramid. It contains the following concepts:

- **Data** is something represented in physical media, such as written text or spoken words. Data exists independently of human beings and can be passed between people.
- **Information** is how we interpret data in our head. For example, when we hear the word *computer*, we have some understanding of what it is.
- **Knowledge** is information being integrated into our world model. For example, once we learn what a computer is, we start having some ideas about how it works, how much it costs, and what it can be used for. This network of interrelated concepts forms our knowledge.
- **Wisdom** is yet one more level of our understanding of the world, and it represents *meta-knowledge*, eg. some notion on how and when the knowledge should be used.

*Image from Wikipedia, By Longlivetheux - Own work, CC BY-SA 4.0*

Thus, the problem of **knowledge representation** is to find some effective way to represent knowledge inside a computer in the form of data, to make it automatically usable. This can be seen as a spectrum:



> Image by Dmitry Soshnikov

- On the left, there are very simple types of knowledge representations that can be effectively used by computers. The simplest one is algorithmic, when knowledge is represented by a computer program. This, however, is not the best way to represent knowledge, because it is not flexible. Knowledge inside our head is often non-algorithmic.
- On the right, there are representations such as natural text. It is the most powerful, but cannot be used for automatic reasoning.

> ✅ Think for a minute about how you represent knowledge in your head and convert it to notes. Is there a particular format that works well for you to aid in retention?

## Classifying Computer Knowledge Representations

We can classify different computer knowledge representation methods in the following categories:

- **Network representations** are based on the fact that we have a network of interrelated concepts inside our head. We can try to reproduce the same networks as a graph inside a computer - a so-called **semantic network**.

1. **Object-Attribute-Value triplets** or **attribute-value pairs**. Since a graph can be represented inside a computer as a list of nodes and edges, we can represent a semantic network by a list of triplets, containing objects, attributes, and values. For example, we build the following triplets about programming languages:

| **Object** | **Attribute** | **Value** |
|---|---|---|
| Python | is | Untyped-Language |
| Python | invented-by | Guido van Rossum |
| Python | block-syntax | indentation |
| Untyped-Language | doesn't have | type definitions |

> ✅ Think how triplets can be used to represent other types of knowledge.

2. **Hierarchical representations** emphasize the fact that we often create a hierarchy of objects inside our head. For example, we know that canary is a bird, and all birds have wings. We also have some idea about what colour canary usually is, and what is their flight speed.

   - **Frame representation** is based on representing each object or class of objects as a **frame** which contains **slots**. Slots have possible default values, value restrictions, or stored procedures that can be called to obtain the value of a slot. All frames form a hierarchy similar to an object hierarchy in object-oriented programming languages.
   - **Scenarios** are special kind of frames that represent complex situations that can unfold in time.

**Python** Slot | Value | Default value | Interval | -----|-------|---------------|----------| Name | Python | | | Is-A | Untyped-Language | | | Variable Case | | CamelCase | | Program Length | | | 5-5000 lines | Block Syntax | Indent | | |

3. **Procedural representations** are based on representing knowledge by a list of actions that can be executed when a certain condition occurs.

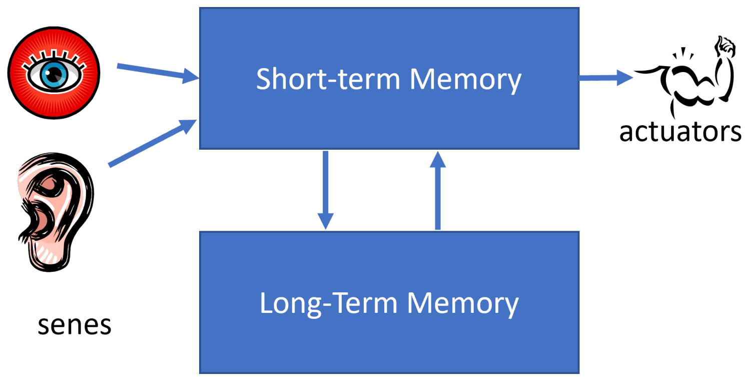
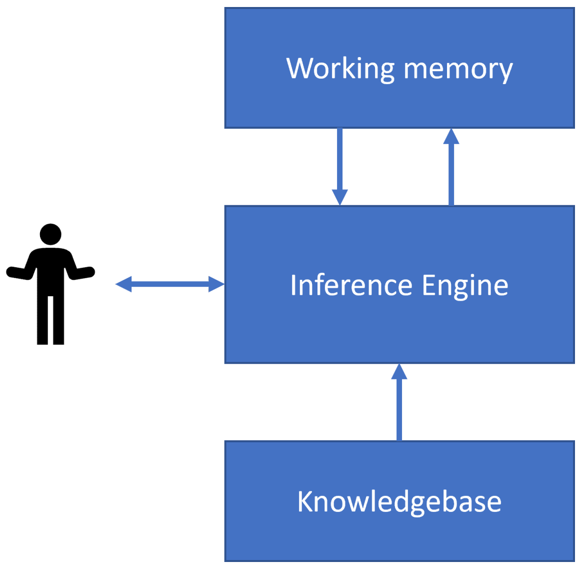
   - Production rules are if-then statements that allow us to draw conclusions. For example, a doctor can have a rule saying that **IF** a patient has high fever **OR** high level of C-reactive protein in blood test **THEN** he has an inflammation. Once we encounter one of the conditions, we can make a conclusion about inflammation, and then use it in further reasoning.
   - Algorithms can be considered another form of procedural representation, although they are almost never used directly in knowledge-based systems.

4. **Logic** was originally proposed by Aristotle as a way to represent universal human knowledge.

   - Predicate Logic as a mathematical theory is too rich to be computable, therefore some subset of it is normally used, such as Horn clauses used in Prolog.
   - Descriptive Logic is a family of logical systems used to represent and reason about hierarchies of objects distributed knowledge representations such as *semantic web*.

## Expert Systems

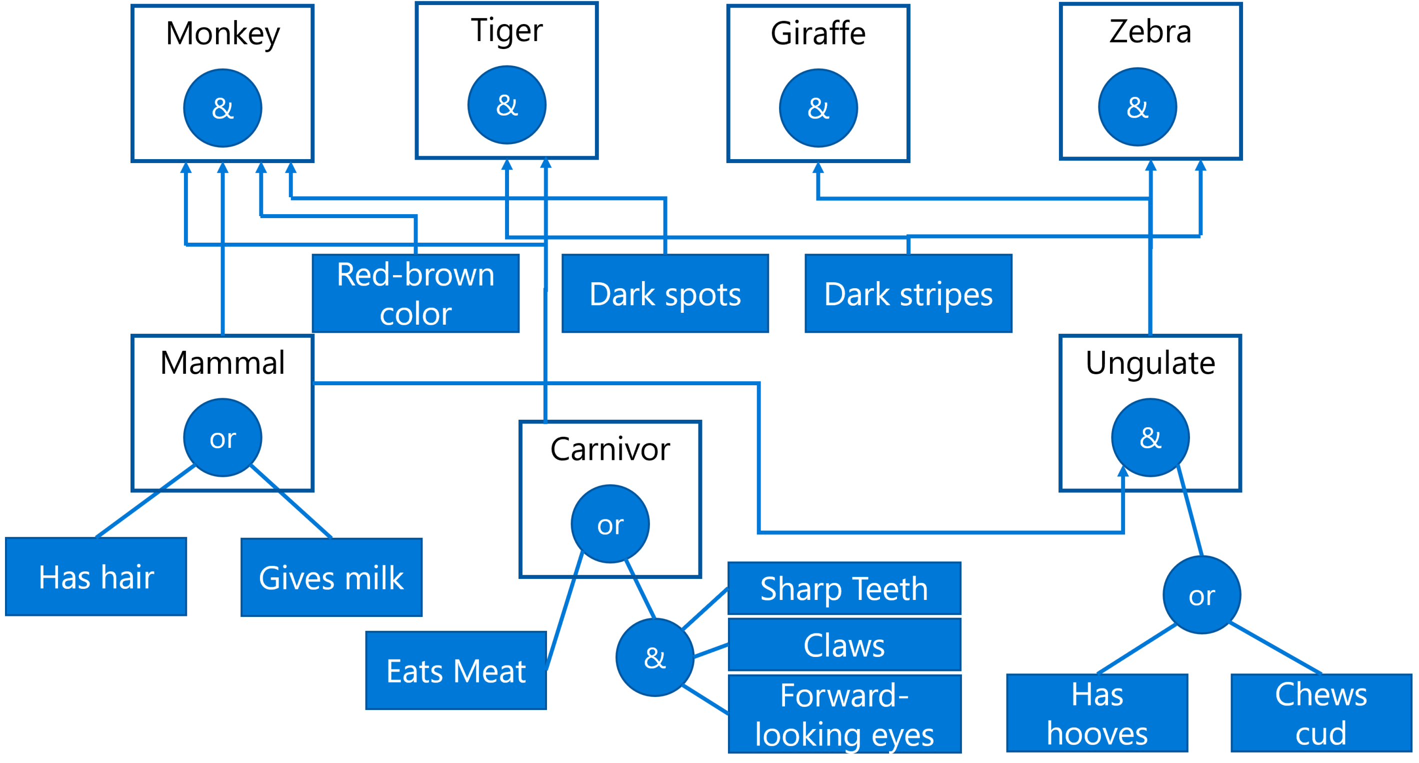
One of the early successes of symbolic AI were so-called **expert systems** - computer systems that were designed to act as an expert in some limited problem domain. They were based on a **knowledge base** extracted from one or more human experts, and they contained an **inference engine** that performed some reasoning on top of it.

|  |  |
|---|---|
| Simplified structure of a human neural system | Architecture of a knowledge-based system |

Expert systems are built like the human reasoning system, which contains **short-term memory** and **long-term memory**. Similarly, in knowledge-based systems we distinguish the following components:

- **Problem memory**: contains the knowledge about the problem being currently solved, i.e. the temperature or blood pressure of a patient, whether he has inflammation or not, etc. This knowledge is also called **static knowledge**, because it contains a snapshot of what we currently know about the problem - the so-called *problem state*.
- **Knowledge base**: represents long-term knowledge about a problem domain. It is extracted manually from human experts, and does not change from consultation to consultation. Because it allows us to navigate from one problem state to another, it is also called **dynamic knowledge**.
- **Inference engine**: orchestrates the whole process of searching in the problem state space, asking questions of the user when necessary. It is also responsible for finding the right rules to be applied to each state.

As an example, let's consider the following expert system of determining an animal based on its physical characteristics:



> Image by Dmitry Soshnikov

This diagram is called an **AND-OR tree**, and it is a graphical representation of a set of production rules. Drawing a tree is useful at the beginning of extracting knowledge from the expert. To represent the knowledge inside the computer it is more convenient to use rules:

```
IF the animal eats meat
OR (animal has sharp teeth
    AND animal has claws
    AND animal has forward-looking eyes
)
THEN the animal is a carnivore
```

You can notice that each condition on the left-hand-side of the rule and the action are essentially object-attribute-value (OAV) triplets. **Working memory** contains the set of OAV triplets that correspond to the problem currently being solved. A **rules engine** looks for rules for which a condition is satisfied and applies them, adding another triplet to the working memory.

> ✅ Write your own AND-OR tree on a topic you like!

## Forward vs. Backward Inference

The process described above is called **forward inference**. It starts with some initial data about the problem available in the working memory, and then executes the following reasoning loop:

1. If the target attribute is present in the working memory - stop and give the result
2. Look for all the rules whose condition is currently satisfied - obtain **conflict set** of rules.
3. Perform **conflict resolution** - select one rule that will be executed on this step. There could be different conflict resolution strategies:
    - Select the first applicable rule in the knowledge base
    - Select a random rule
    - Select a *more specific* rule, i.e. the one meeting the most conditions in the "left-hand-side" (LHS)
4. Apply selected rule and insert new piece of knowledge into the problem state
5. Repeat from step 1.

However, in some cases we might want to start with an empty knowledge about the problem, and ask questions that will help us arrive to the conclusion. For example, when doing medical diagnosis, we usually do not perform all medical analyses in advance before starting diagnosing the patient. We rather want to perform analyses when a decision needs to be made.

This process can be modeled using **backward inference**. It is driven by the **goal** - the attribute value that we are looking to find:

1. Select all rules that can give us the value of a goal (i.e. with the goal on the RHS ("right-hand-side")) - a conflict set
2. If there are no rules for this attribute, or there is a rule saying that we should ask the value from the user - ask for it, otherwise:
3. Use conflict resolution strategy to select one rule that we will use as *hypothesis* - we will try to prove it
4. Recurrently repeat the process for all attributes in the LHS of the rule, trying to prove them as goals
5. If at any point the process fails - use another rule at step 3.

> ✅ In which situations is forward inference more appropriate? How about backward inference?

## Implementing Expert Systems

Expert systems can be implemented using different tools:

- Programming them directly in some high level programming language. This is not the best idea, because the main advantage of a knowledge-based system is that knowledge is separated from inference, and potentially a problem domain expert should be able to write rules without understanding the details of the inference process
- Using **expert systems shell**, i.e. a system specifically designed to be populated by knowledge using some knowledge representation language.

## ✍️ Exercise: Animal Inference

See Animals.ipynb for an example of implementing forward and backward inference expert system.

> **Note**: This example is rather simple, and only gives the idea of how an expert system looks like. Once you start creating such a system, you will only notice some intelligent behaviour from it once you reach certain number of rules, around 200+. At some point, rules become too complex to keep all of them in mind, and at this point you may start wondering why a system makes certain decisions. However, the important characteristics of knowledge-based systems is that you can always explain exactly how any of the decisions were made.

## Ontologies and the Semantic Web

At the end of 20th century there was an initiative to use knowledge representation to annotate Internet resources, so that it would be possible to find resources that correspond to very specific queries. This motion was called **Semantic Web**, and it relied on several concepts:

- A special knowledge representation based on **description logics** (DL). It is similar to frame knowledge representation, because it builds a hierarchy of objects with properties, but it has formal logical semantics and inference. There is a whole family of DLs which balance between expressiveness and algorithmic complexity of inference.
- Distributed knowledge representation, where all concepts are represented by a global URI identifier, making it possible to create knowledge hierarchies that span the internet.
- A family of XML-based languages for knowledge description: RDF (Resource Description Framework), RDFS (RDF Schema), OWL (Ontology Web Language).

A core concept in the Semantic Web is a concept of **Ontology**. It refers to a explicit specification of a problem domain using some formal knowledge representation. The simplest ontology can be just a hierarchy of objects in a problem domain, but more complex ontologies will include rules that can be used for inference.

In the semantic web, all representations are based on triplets. Each object and each relation are uniquely identified by the URI. For example, if we want to state the fact that this AI Curriculum has been developed by Dmitry Soshnikov on Jan 1st, 2022 - here are the triplets we can use:

```
http://github.com/microsoft/ai-for-beginners http://www.example.com/terms/
http://github.com/microsoft/ai-for-beginners http://purl.org/dc/elements/1
```

> ✅ Here `http://www.example.com/terms/creation-date` and `http://purl.org/dc/elements/1.1/creator` are some well-known and universally accepted URIs to express the concepts of creator and creation date.

In a more complex case, if we want to define a list of creators, we can use some data structures defined in RDF.

> Diagrams above by Dmitry Soshnikov

The progress of building the Semantic Web was somehow slowed down by the success of search engines and natural language processing techniques, which allow extracting structured data from text. However, in some areas there are still significant efforts to maintain ontologies and knowledge bases. A few projects worth noting:

- WikiData is a collection of machine readable knowledge bases associated with Wikipedia. Most of the data is mined from Wikipedia *InfoBoxes*, pieces of structured content inside Wikipedia pages. You can query wikidata in SPARQL, a special query language for Semantic Web. Here is a sample query that displays most popular eye colors among humans:

```sparql
#defaultView:BubbleChart
SELECT ?eyeColorLabel (COUNT(?human) AS ?count)
WHERE
{
  ?human wdt:P31 wd:Q5.       # human instance-of homo sapiens
  ?human wdt:P1340 ?eyeColor. # human eye-color ?eyeColor
  SERVICE wikibase:label { bd:serviceParam wikibase:language "en". }
}
GROUP BY ?eyeColorLabel
```

- DBpedia is another effort similar to WikiData.

> ✅ If you want to experiment with building your own ontologies, or opening existing ones, there is a great visual ontology editor called Protégé. Download it, or use it online.

*Web Protégé editor open with the Romanov Family ontology. Screenshot by Dmitry Soshnikov*

## ✍️ Exercise: A Family Ontology

See FamilyOntology.ipynb for an example of using Semantic Web techniques to reason about family relationships. We will take a family tree represented in common GEDCOM format and an ontology of family relationships and build a graph of all family relationships for given set of individuals.

## Microsoft Concept Graph

In most of the cases, ontologies are carefully created by hand. However, it is also possible to **mine** ontologies from unstructured data, for example, from natural language texts.

One such attempt was done by Microsoft Research, and resulted in Microsoft Concept Graph.

It is a large collection of entities grouped together using `is-a` inheritance relationship. It allows answering questions like "What is Microsoft?" - the answer being something like "a company with probability 0.87, and a brand with probability 0.75".

The Graph is available either as REST API, or as a large downloadable text file that lists all entity pairs.

## ✍️ Exercise: A Concept Graph

Try the MSConceptGraph.ipynb notebook to see how we can use Microsoft Concept Graph to group news articles into several categories.

## Conclusion

Nowadays, AI is often considered to be a synonym for *Machine Learning* or *Neural Networks*. However, a human being also exhibits explicit reasoning, which is something currently not being handled by neural networks. In real world projects, explicit reasoning is still used to perform tasks that require explanations, or being able to modify the behavior of the system in a controlled way.

## 🚀 Challenge

In the Family Ontology notebook associated to this lesson, there is an opportunity to experiment with other family relations. Try to discover new connections between people in the family tree.

## Post-lecture quiz

## Review & Self Study

Do some research on the internet to discover areas where humans have tried to quantify and codify knowledge. Take a look at Bloom's Taxonomy, and go back in history to learn how humans tried to make sense of their world. Explore the work of Linnaeus to create a taxonomy of organisms, and observe the way Dmitri Mendeleev created a way for chemical elements to be described and grouped. What other interesting examples can you find?

**Assignment**: Build an Ontology

# Introduction to Neural Networks: Perceptron

## Pre-lecture quiz

One of the first attempts to implement something similar to a modern neural network was done by Frank Rosenblatt from Cornell Aeronautical Laboratory in 1957. It was a hardware implementation called "Mark-1", designed to recognize primitive geometric figures, such as triangles, squares and circles.

| | |
|---|---|
| Frank Rosenblatt | The Mark 1 Perceptron |

> Images from Wikipedia

An input image was represented by 20x20 photocell array, so the neural network had 400 inputs and one binary output. A simple network contained one neuron, also called a **threshold logic unit**. Neural network weights acted like potentiometers that required manual adjustment during the training phase.

> ✅ A potentiometer is a device that allows the user to adjust the resistance of a circuit.

> The New York Times wrote about perceptron at that time: the embryo of an electronic computer that [the Navy] expects will be able to walk, talk, see, write, reproduce itself and be conscious of its existence.

## Perceptron Model

Suppose we have N features in our model, in which case the input vector would be a vector of size N. A perceptron is a **binary classification** model, i.e. it can distinguish between two classes of input data. We will assume that for each input vector x the output of our perceptron would be either +1 or -1, depending on the class. The output will be computed using the formula:

$y(x) = f(w^T x)$

where f is a step activation function

## Training the Perceptron

To train a perceptron we need to find a weights vector w that classifies most of the values correctly, i.e. results in the smallest **error**. This error is defined by **perceptron criterion** in the following manner:

$E(w) = -\sum w^T x_i t_i$

where:

- the sum is taken on those training data points i that result in the wrong classification
- $x_i$ is the input data, and $t_i$ is either -1 or +1 for negative and positive examples accordingly.

This criteria is considered as a function of weights w, and we need to minimize it. Often, a method called **gradient descent** is used, in which we start with some initial weights $w^{(0)}$, and then at each step update the weights according to the formula:

$w^{(t+1)} = w^{(t)} - \eta\nabla E(w)$

Here η is the so-called **learning rate**, and ∇E(w) denotes the **gradient** of E. After we calculate the gradient, we end up with

$w^{(t+1)} = w^{(t)} + \sum \eta x_i t_i$

The algorithm in Python looks like this:

```python
def train(positive_examples, negative_examples, num_iterations = 100, eta =

    weights = [0,0,0] # Initialize weights (almost randomly :)

    for i in range(num_iterations):
        pos = random.choice(positive_examples)
        neg = random.choice(negative_examples)

        z = np.dot(pos, weights) # compute perceptron output
        if z < 0: # positive example classified as negative
            weights = weights + eta*weights.shape

        z  = np.dot(neg, weights)
        if z >= 0: # negative example classified as positive
            weights = weights - eta*weights.shape

    return weights
```

## Conclusion

In this lesson, you learned about a perceptron, which is a binary classification model, and how to train it by using a weights vector.

## 🚀 Challenge

If you'd like to try to build your own perceptron, try this lab on Microsoft Learn which uses the Azure ML designer.

## Post-lecture quiz

## Review & Self Study

To see how we can use perceptron to solve a toy problem as well as real-life problems, and to continue learning - go to Perceptron notebook.

Here's an interesting article about perceptrons as well.

## Assignment

In this lesson, we have implemented a perceptron for binary classification task, and we have used it to classify between two handwritten digits. In this lab, you are asked to solve the problem of digit classification entirely, i.e. determine which digit is most likely to correspond to a given image.

- Instructions
- Notebook

# Introduction to Neural Networks. Multi-Layered Perceptron

In the previous section, you learned about the simplest neural network model - one-layered perceptron, a linear two-class classification model.

In this section we will extend this model into a more flexible framework, allowing us to:

- perform **multi-class classification** in addition to two-class
- solve **regression problems** in addition to classification
- separate classes that are not linearly separable

We will also develop our own modular framework in Python that will allow us to construct different neural network architectures.

## Pre-lecture quiz

---

## Formalization of Machine Learning

---

Let's start with formalizing the Machine Learning problem. Suppose we have a training dataset **X** with labels **Y**, and we need to build a model *f* that will make most accurate predictions. The quality of predictions is measured by **Loss function** $\mathcal{L}$. The following loss functions are often used:

- For regression problem, when we need to predict a number, we can use **absolute error** $\sum_i|f(x^{(i)})-y^{(i)}|$, or **squared error** $\sum_i(f(x^{(i)})-y^{(i)})^2$
- For classification, we use **0-1 loss** (which is essentially the same as **accuracy** of the model), or **logistic loss**.

For one-level perceptron, function *f* was defined as a linear function $f(x)=wx+b$ (here *w* is the weight matrix, *x* is the vector of input features, and *b* is bias vector). For different neural network architectures, this function can take more complex form.

> In the case of classification, it is often desirable to get probabilities of corresponding classes as network output. To convert arbitrary numbers to probabilities (eg. to normalize the output), we often use **softmax** function σ, and the function f becomes $f(x)=\sigma(wx+b)$

In the definition of *f* above, *w* and *b* are called **parameters** $\theta=\langle w,b\rangle$. Given the dataset $\langle \mathbf{X},\mathbf{Y}\rangle$, we can compute an overall error on the whole dataset as a function of parameters θ.

> ✅ **The goal of neural network training is to minimize the error by varying parameters θ**

## Gradient Descent Optimization

There is a well-known method of function optimization called **gradient descent**. The idea is that we can compute a derivative (in multi-dimensional case call **gradient**) of loss function with respect to parameters, and vary parameters in such a way that the error would decrease. This can be formalized as follows:

- Initialize parameters by some random values $w^{(0)}$, $b^{(0)}$
- Repeat the following step many times:
  - $w^{(i+1)} = w^{(i)}-\eta\partial\mathcal{L}/\partial w$
  - $b^{(i+1)} = b^{(i)}-\eta\partial\mathcal{L}/\partial b$

During training, the optimization steps are supposed to be calculated considering the whole dataset (remember that loss is calculated as a sum through all training samples). However, in real life we take small portions of the dataset called **minibatches**, and calculate gradients based on a subset of data. Because subset is taken randomly each time, such method is called **stochastic gradient descent** (SGD).

## Multi-Layered Perceptrons and Backpropagation

One-layer network, as we have seen above, is capable of classifying linearly separable classes. To build a richer model, we can combine several layers of the network. Mathematically it would mean that the function *f* would have a more complex form, and will be computed in several steps:

- $z_1=w_1x+b_1$
- $z_2=w_2\alpha(z_1)+b_2$
- $f = \sigma(z_2)$

Here, α is a **non-linear activation function**, σ is a softmax function, and parameters θ= <*$w_1$,$b_1$,$w_2$,$b_2$*>.

The gradient descent algorithm would remain the same, but it would be more difficult to calculate gradients. Given the chain differentiation rule, we can calculate derivatives as:

- $\partial\mathcal{L}/\partial w_2 = (\partial\mathcal{L}/\partial\sigma)(\partial\sigma/\partial z_2)(\partial z_2/\partial w_2)$
- $\partial\mathcal{L}/\partial w_1 = (\partial\mathcal{L}/\partial\sigma)(\partial\sigma/\partial z_2)(\partial z_2/\partial\alpha)(\partial\alpha/\partial z_1)(\partial z_1/\partial w_1)$

> ✅ The chain differentiation rule is used to calculate derivatives of the loss function with respect to parameters.

Note that the left-most part of all those expressions is the same, and thus we can effectively calculate derivatives starting from the loss function and going "backwards" through the computational graph. Thus the method of training a multi-layered perceptron is called **backpropagation**, or 'backprop'.

compute graph

> TODO: image citation

> ✅ We will cover backprop in much more detail in our notebook example.

## Conclusion

In this lesson, we have built our own neural network library, and we have used it for a simple two-dimensional classification task.

## 🚀 Challenge

In the accompanying notebook, you will implement your own framework for building and training multi-layered perceptrons. You will be able to see in detail how modern neural networks operate.

Proceed to the OwnFramework notebook and work through it.

## Post-lecture quiz

## Review & Self Study

Backpropagation is a common algorithm used in AI and ML, worth studying in more detail

## Assignment

In this lab, you are asked to use the framework you constructed in this lesson to solve MNIST handwritten digit classification.

- Instructions
- Notebook

# Neural Network Frameworks

As we have learned already, to be able to train neural networks efficiently we need to do two things:

- To operate on tensors, eg. to multiply, add, and compute some functions such as sigmoid or softmax
- To compute gradients of all expressions, in order to perform gradient descent optimization

## Pre-lecture quiz

While the `numpy` library can do the first part, we need some mechanism to compute gradients. In our framework that we have developed in the previous section we had to manually program all derivative functions inside the `backward` method, which does backpropagation. Ideally, a framework should give us the opportunity to compute gradients of *any expression* that we can define.

Another important thing is to be able to perform computations on GPU, or any other specialized compute units, such as TPU. Deep neural network training requires *a lot* of computations, and to be able to parallelize those computations on GPUs is very important.

> ✅ The term 'parallelize' means to distribute the computations over multiple devices.

Currently, the two most popular neural frameworks are: TensorFlow and PyTorch. Both provide a low-level API to operate with tensors on both CPU and GPU. On top of the low-level API, there is also higher-level API, called Keras and PyTorch Lightning correspondingly.

| Low-Level API | TensorFlow | PyTorch |
|---|---|---|
| High-level API | Keras | PyTorch Lightning |

**Low-level APIs** in both frameworks allow you to build so-called **computational graphs**. This graph defines how to compute the output (usually the loss function) with given input parameters, and can be pushed for computation on GPU, if it is available. There are functions to differentiate this computational graph and compute gradients, which can then be used for optimizing model parameters.

**High-level APIs** pretty much consider neural networks as a **sequence of layers**, and make constructing most of the neural networks much easier. Training the model usually requires preparing the data and then calling a `fit` function to do the job.

The high-level API allows you to construct typical neural networks very quickly without worrying about lots of details. At the same time, low-level API offer much more control over the training process, and thus they are used a lot in research, when you are dealing with new neural network architectures.

It is also important to understand that you can use both APIs together, eg. you can develop your own network layer architecture using low-level API, and then use it inside the larger network constructed and trained with the high-level API. Or you can define a network using the high-level API as a sequence of layers, and then use your own low-level training loop to perform optimization. Both APIs use the same basic underlying concepts, and they are designed to work well together.

## Learning

In this course, we offer most of the content both for PyTorch and TensorFlow. You can choose your preferred framework and only go through the corresponding notebooks. If you are not sure which framework to choose, read some discussions on the internet regarding **PyTorch vs. TensorFlow**. You can also have a look at both frameworks to get better understanding.

Where possible, we will use High-Level APIs for simplicity. However, we believe it is important to understand how neural networks work from the ground up, thus in the beginning we start by working with low-level API and tensors. However, if you want to get going fast and do not want to spend a lot of time on learning these details, you can skip those and go straight into high-level API notebooks.

## ✍️ Exercises: Frameworks

Continue your learning in the following notebooks:

| Low-Level API | TensorFlow+Keras Notebook | PyTorch |
|---|---|---|
| High-level API | Keras | *PyTorch Lightning* |

After mastering the frameworks, let's recap the notion of overfitting.

# Introduction to Computer Vision

Computer Vision is a discipline whose aim is to allow computers to gain high-level understanding of digital images. This is quite a broad definition, because *understanding* can mean many different things, including finding an object on a picture (**object detection**), understanding what is happening (**event detection**), describing a picture in text, or reconstructing a scene in 3D. There are also special tasks related to human images: age and emotion estimation, face detection and identification, and 3D pose estimation, to name a few.

## Pre-lecture quiz

One of the simplest tasks of computer vision is **image classification**.

Computer vision is often considered to be a branch of AI. Nowadays, most of computer vision tasks are solved using neural networks. We will learn more about the special type of neural networks used for computer vision, convolutional neural networks, throughout this section.

However, before you pass the image to a neural network, in many cases it makes sense to use some algorithmic techniques to enhance the image.

There are several Python libraries available for image processing:

- **imageio** can be used for reading/writing different image formats. It also support ffmpeg, a useful tool to convert video frames to images.
- **Pillow** (also known as PIL) is a bit more powerful, and also supports some image manipulation such as morphing, palette adjustments, and more.
- **OpenCV** is a powerful image processing library written in C++, which has become the *de facto* standard for image processing. It has a convenient Python interface.
- **dlib** is a C++ library that implements many machine learning algorithms, including some of the Computer Vision algorithms. It also has a Python interface, and can be used for challenging tasks such as face and facial landmark detection.

# OpenCV

OpenCV is considered to be the *de facto* standard for image processing. It contains a lot of useful algorithms, implemented in C++. You can call OpenCV from Python as well.

A good place to learn OpenCV is this Learn OpenCV course. In our curriculum, our goal is not to learn OpenCV, but to show you some examples when it can be used, and how.

## Loading Images

Images in Python can be conveniently represented by NumPy arrays. For example, grayscale images with the size of 320x200 pixels would be stored in a 200x320 array, and color images of the same dimension would have shape of 200x320x3 (for 3 color channels). To load an image, you can use the following code:

```python
import cv2
import matplotlib.pyplot as plt

im = cv2.imread('image.jpeg')
plt.imshow(im)
```

Traditionally, OpenCV uses BGR (Blue-Green-Red) encoding for color images, while the rest of Python tools use the more traditional RGB (Red-Green-Blue). For the image to look right, you need to convert it to the RGB color space, either by swapping dimensions in the NumPy array, or by calling an OpenCV function:

```python
im = cv2.cvtColor(im,cv2.COLOR_BGR2RGB)
```

The same `cvtColor` function can be used to perform other color space transformations such as converting an image to grayscale or to the HSV (Hue-Saturation-Value) color space.

You can also use OpenCV to load video frame-by-frame - an example is given in the exercise OpenCV Notebook.

## Image Processing

Before feeding an image to a neural network, you may want to apply several pre-processing steps. OpenCV can do many things, including:

- **Resizing** the image using
  `im = cv2.resize(im, (320,200),interpolation=cv2.INTER_LANCZOS)`
- **Blurring** the image using `im = cv2.medianBlur(im,3)` or
  `im = cv2.GaussianBlur(im, (3,3), 0)`
- Changing the **brightness and contrast** of the image can be done by NumPy array manipulations, as described in this Stackoverflow note.
- Using thresholding by calling `cv2.threshold` / `cv2.adaptiveThreshold` functions, which is often preferable to adjusting brightness or contrast.
- Applying different transformations to the image:
  - **Affine transformations** can be useful if you need to combine rotation, resizing and skewing to the image and you know the source and destination location of three points in the image. Affine transformations keep parallel lines parallel.
  - **Perspective transformations** can be useful when you know the source and destination positions of 4 points in the image. For example, if you take a picture of a rectangular document via a smartphone camera from some angle, and you want to make a rectangular image of the document itself.
- Understanding movement inside the image by using **optical flow**.

## Examples of using Computer Vision

In our OpenCV Notebook, we give some examples of when computer vision can be used to perform specific tasks:

- **Pre-processing a photograph of a Braille book**. We focus on how we can use thresholding, feature detection, perspective transformation and NumPy manipulations to separate individual Braille symbols for further classification by a neural network.

Braille Image

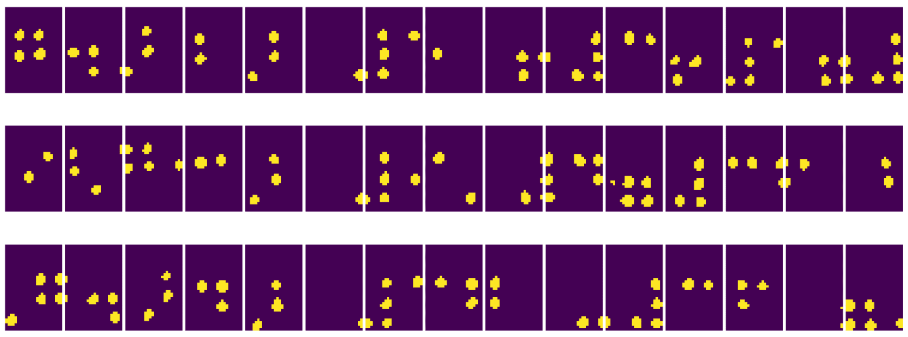
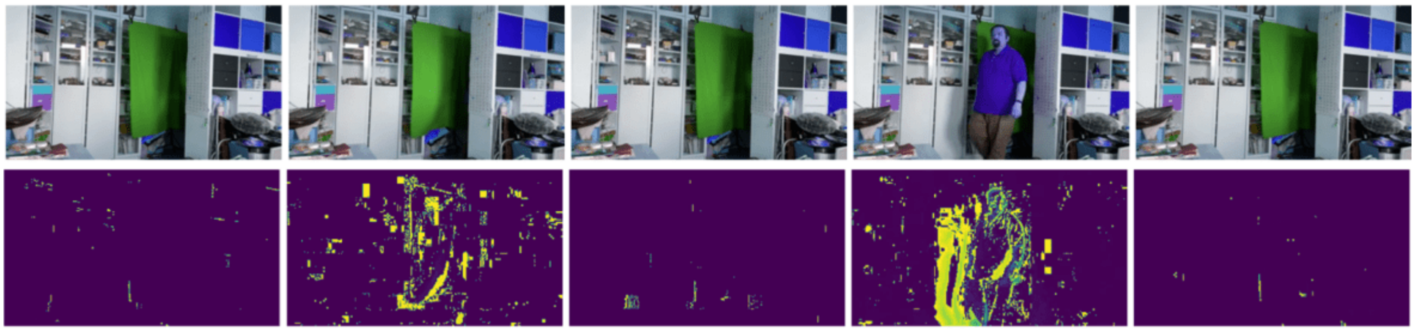


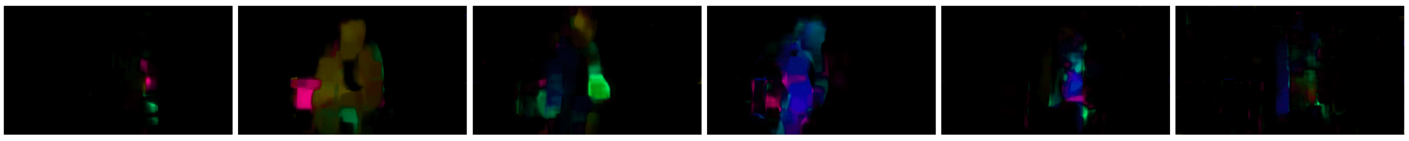
Image from OpenCV.ipynb

- **Detecting motion in video using frame difference**. If the camera is fixed, then frames from the camera feed should be pretty similar to each other. Since frames are represented as arrays, just by subtracting those arrays for two subsequent frames we will get the pixel difference, which should be low for static frames, and become higher once there is substantial motion in the image.



> Image from OpenCV.ipynb

- **Detecting motion using Optical Flow**. Optical flow allows us to understand how individual pixels on video frames move. There are two types of optical flow:
    - **Dense Optical Flow** computes the vector field that shows for each pixel where is it moving
    - **Sparse Optical Flow** is based on taking some distinctive features in the image (eg. edges), and building their trajectory from frame to frame.



> Image from OpenCV.ipynb

## ✍️ Example Notebooks: OpenCVtry OpenCV in Action

Let's do some experiments with OpenCV by exploring OpenCV Notebook

## Conclusion

Sometimes, relatively complex tasks such as movement detection or fingertip detection can be solved purely by computer vision. Thus, it is very helpful to know the basic techniques of computer vision, and what libraries like OpenCV can do.

## 🚀 Challenge

Watch this video from the AI show to learn about the Cortic Tigers project and how they built a block-based solution to democratize computer vision tasks via a robot. Do some research on other projects like this that help onboard new learners into the field.

## Post-lecture quiz

## Review & Self Study

Read more on optical flow in this great tutorial.

## Assignment

In this lab, you will take a video with simple gestures, and your goal is to extract up/down/left/right movements using optical flow.

Palm Movement Frame

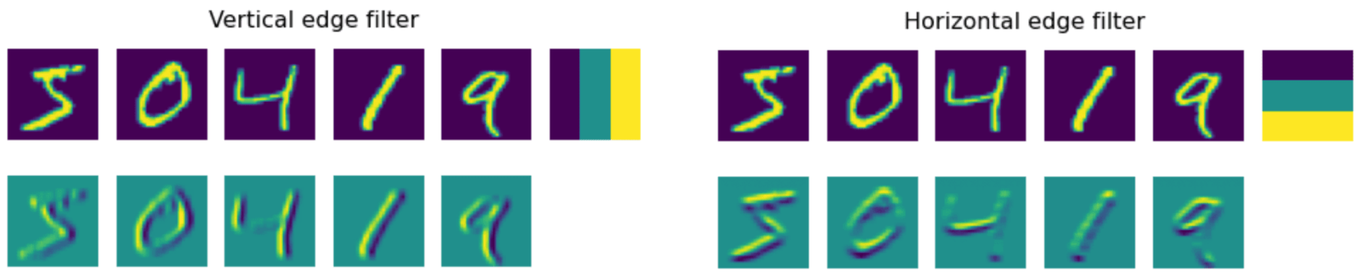
# Convolutional Neural Networks

We have seen before that neural networks are quite good at dealing with images, and even one-layer perceptron is able to recognize handwritten digits from MNIST dataset with reasonable accuracy. However, the MNIST dataset is very special, and all digits are centered inside the image, which makes the task simpler.

## Pre-lecture quiz

In real life, we want to be able to recognize objects on a picture regardless of their exact location in the image. Computer vision is different from generic classification, because when we are trying to find a certain object in the picture, we are scanning the image looking for some specific **patterns** and their combinations. For example, when looking for a cat, we first may look for horizontal lines, which can form whiskers, and then certain a combination of whiskers can tell us that it is actually a picture of a cat. Relative position and presence of certain patterns is important, and not their exact position on the image.

To extract patterns, we will use the notion of **convolutional filters**. As you know, an image is represented by a 2D-matrix, or a 3D-tensor with color depth. Applying a filter means that we take relatively small **filter kernel** matrix, and for each pixel in the original image we compute the weighted average with neighboring points. We can view this like a small window sliding over the whole image, and averaging out all pixels according to the weights in the filter kernel matrix.



> Image by Dmitry Soshnikov

For example, if we apply 3x3 vertical edge and horizontal edge filters to the MNIST digits, we can get highlights (e.g. high values) where there are vertical and horizontal edges in our original image. Thus those two filters can be used to "look for" edges. Similarly, we can design different filters to look for other low-level patterns:

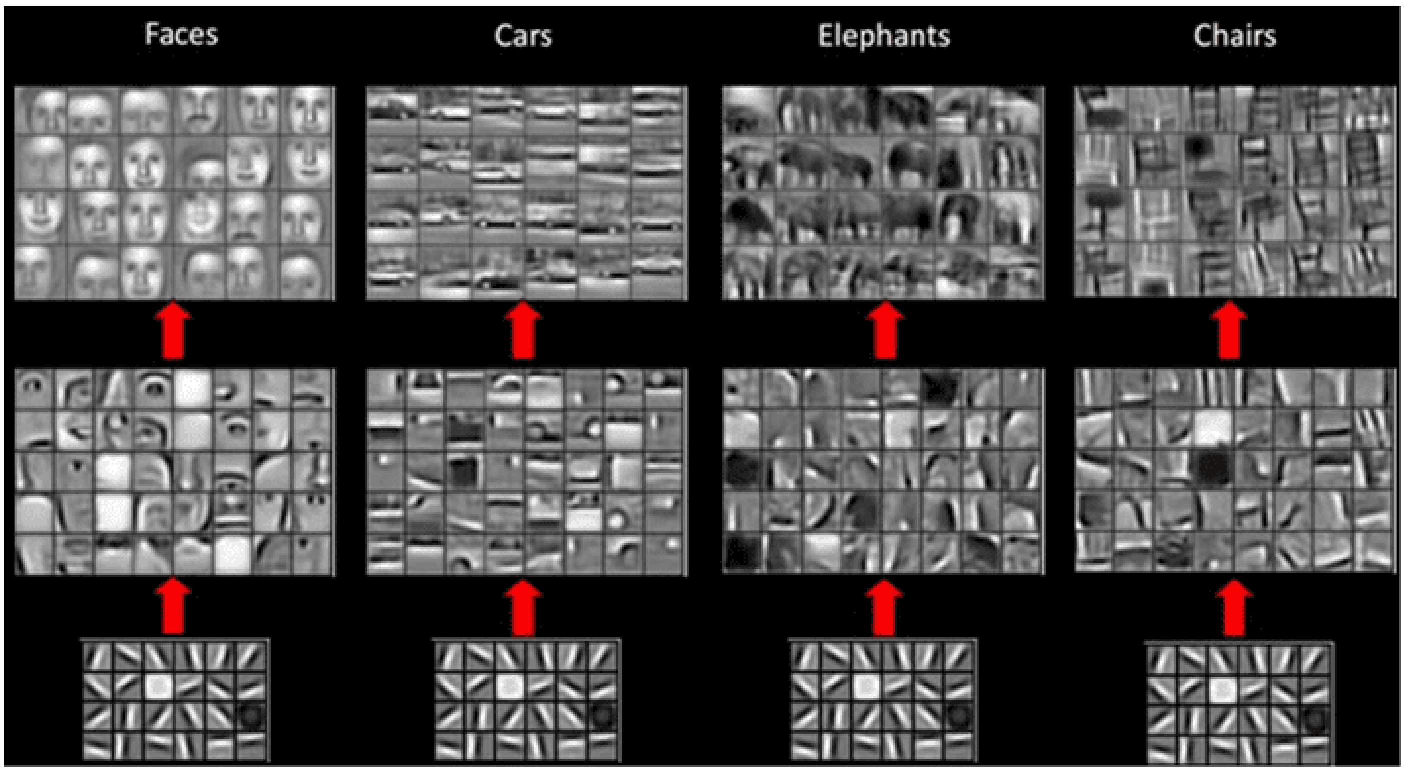
> Image of Leung-Malik Filter Bank

However, while we can design the filters to extract some patterns manually, we can also design the network in such a way that it will learn the patterns automatically. It is one of the main ideas behind the CNN.

## Main ideas behind CNN

The way CNNs work is based on the following important ideas:

- Convolutional filters can extract patterns
- We can design the network in such a way that filters are trained automatically
- We can use the same approach to find patterns in high-level features, not only in the original image. Thus CNN feature extraction work on a hierarchy of features, starting from low-level pixel combinations, up to higher level combination of picture parts.



> Image from a paper by Hislop-Lynch, based on their research

## ✍️ Exercises: Convolutional Neural Networks

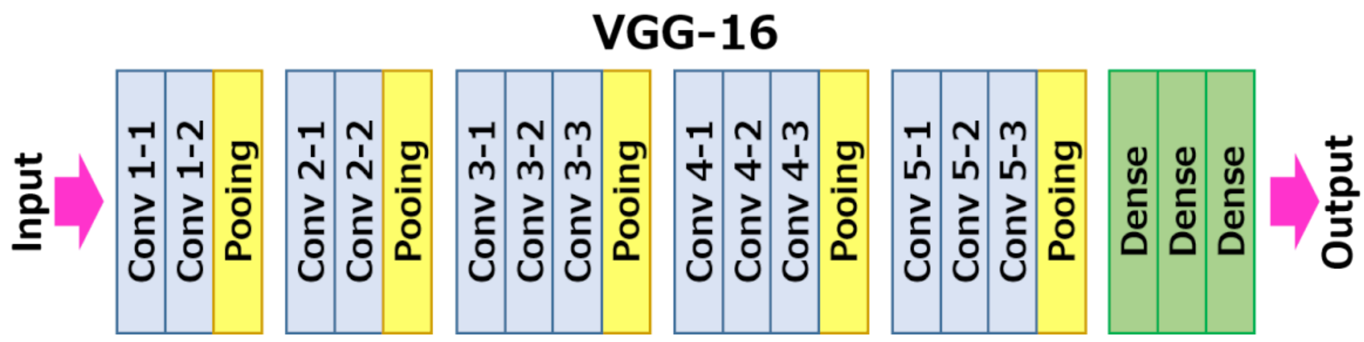
Let's continue exploring how convolutional neural networks work, and how we can achieve trainable filters, by working through the corresponding notebooks:

- Convolutional Neural Networks - PyTorch
- Convolutional Neural Networks - TensorFlow

## Pyramid Architecture

Most of the CNNs used for image processing follow a so-called pyramid architecture. The first convolutional layer applied to the original images typically has a relatively low number of filters (8-16), which correspond to different pixel combinations, such as horizontal/vertical lines of strokes. At the next level, we reduce the spatial dimension of the network, and increase the number of filters, which corresponds to more possible combinations of simple features. With each layer, as we move towards the final classifier, spatial dimensions of the image decrease, and the number of filters grow.

As an example, let's look at the architecture of VGG-16, a network that achieved 92.7% accuracy in ImageNet's top-5 classification in 2014:



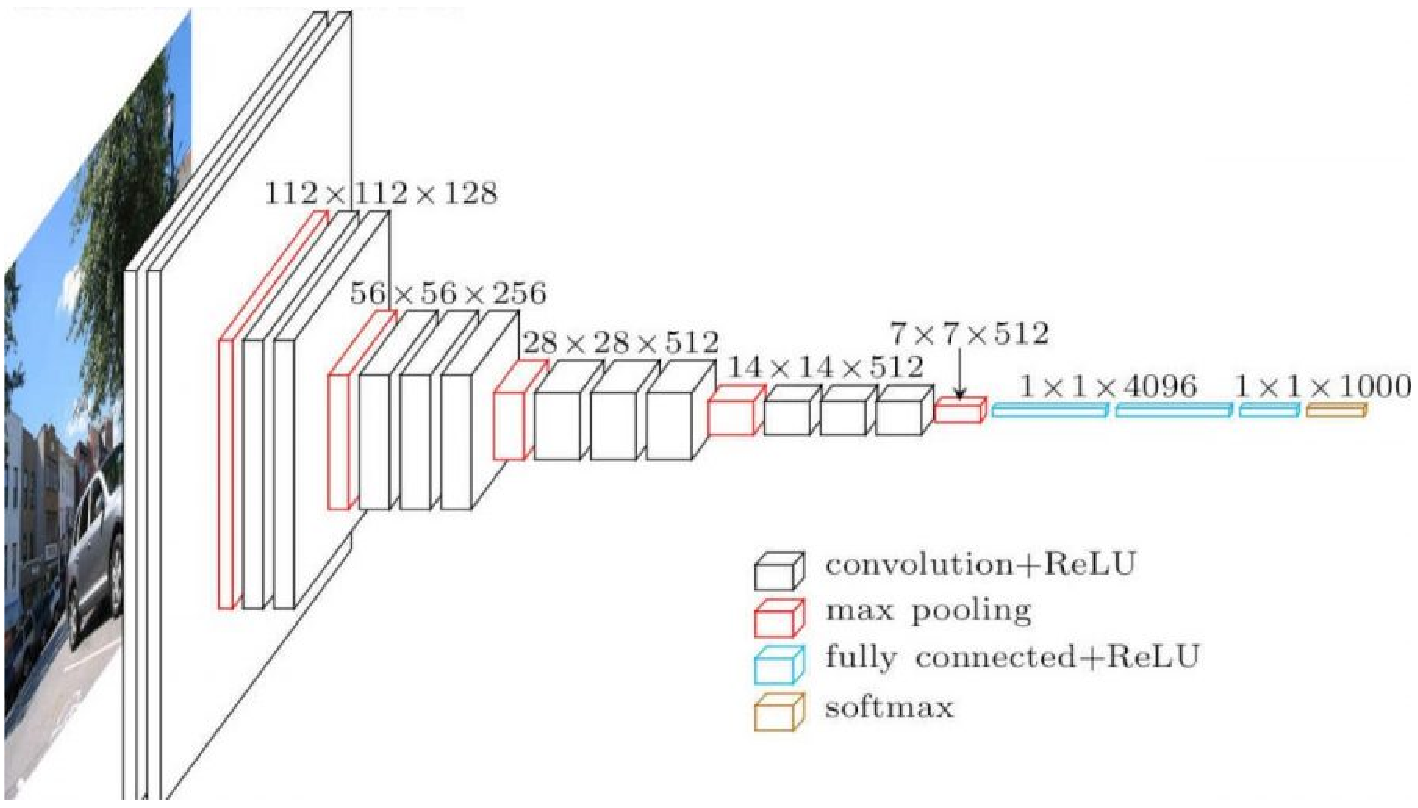


Image from Researchgate

## Best-Known CNN Architectures

Continue your study about the best-known CNN architectures

# Pre-trained Networks and Transfer Learning

Training CNNs can take a lot of time, and a lot of data is required for that task. However, much of the time is spent learning the best low-level filters that a network can use to extract patterns from images. A natural question arises - can we use a neural network trained on one dataset and adapt it to classify different images without requiring a full training process?

## Pre-lecture quiz

This approach is called **transfer learning**, because we transfer some knowledge from one neural network model to another. In transfer learning, we typically start with a pre-trained model, which has been trained on some large image dataset, such as **ImageNet**. Those models can already do a good job extracting different features from generic images, and in many cases just building a classifier on top of those extracted features can yield a good result.

> ✅ Transfer Learning is a term you find in other academic fields, such as Education. It refers to the process of taking knowledge from one domain and applying it to another.

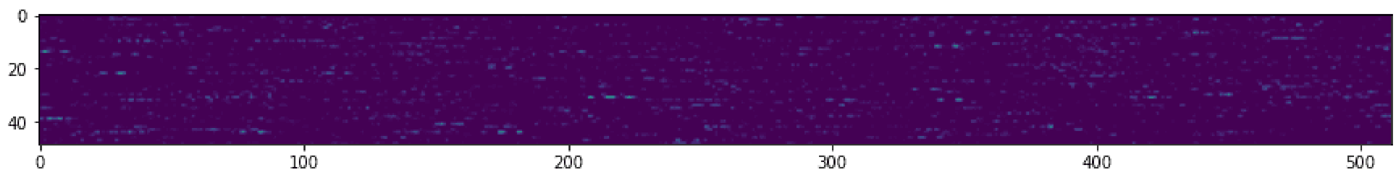
## Pre-Trained Models as Feature Extractors

The convolutional networks that we have talked about in the previous section contained a number of layers, each of which is supposed to extract some features from the image, starting from low-level pixel combinations (such as horizontal/vertical line or stroke), up to higher level combinations of features, corresponding to things like an eye of a flame. If we train CNN on sufficiently large dataset of generic and diverse images, the network should learn to extract those common features.

Both Keras and PyTorch contain functions to easily load pre-trained neural network weights for some common architectures, most of which were trained on ImageNet images. The most often used ones are described on the CNN Architectures page from the prior lesson. In particular, you may want to consider using one of the following:

- **VGG-16/VGG-19** which are relatively simple models that still give good accuracy. Often using VGG as a first attempt is a good choice to see how transfer learning is working.
- **ResNet** is a family of models proposed by Microsoft Research in 2015. They have more layers, and thus take more resources.
- **MobileNet** is a family of models with reduced size, suitable for mobile devices. Use them if you are short in resources and can sacrifice a little bit of accuracy.

Here are sample features extracted from a picture of a cat by VGG-16 network:



## Cats vs. Dogs Dataset

In this example, we will use a dataset of Cats and Dogs, which is very close to a real-life image classification scenario.

## ✍️ Exercise: Transfer Learning

Let's see transfer learning in action in corresponding notebooks:

- Transfer Learning - PyTorch
- Transfer Learning - TensorFlow

## Conclusion

Using transfer learning, you are able to quickly put together a classifier for a custom object classification task and achieve high accuracy. You can see that more complex tasks that we are solving now require higher computational power, and cannot be easily solved on the CPU. In the next unit, we will try to use a more lightweight implementation to train the same model using lower compute resources, which results in just slightly lower accuracy.

## 🚀 Challenge

In the accompanying notebooks, there are notes at the bottom about how transfer knowledge works best with somewhat similar training data (a new type of animal, perhaps). Do some experimentation with completely new types of images to see how well or poorly your transfer knowledge models perform.

## Post-lecture quiz

## Review & Self Study

Read through TrainingTricks.md to deepen your knowledge of some other way to train your models.

## Assignment

In this lab, we will use real-life Oxford-IIIT pets dataset with 35 breeds of cats and dogs, and we will build a transfer learning classifier.

# Autoencoders

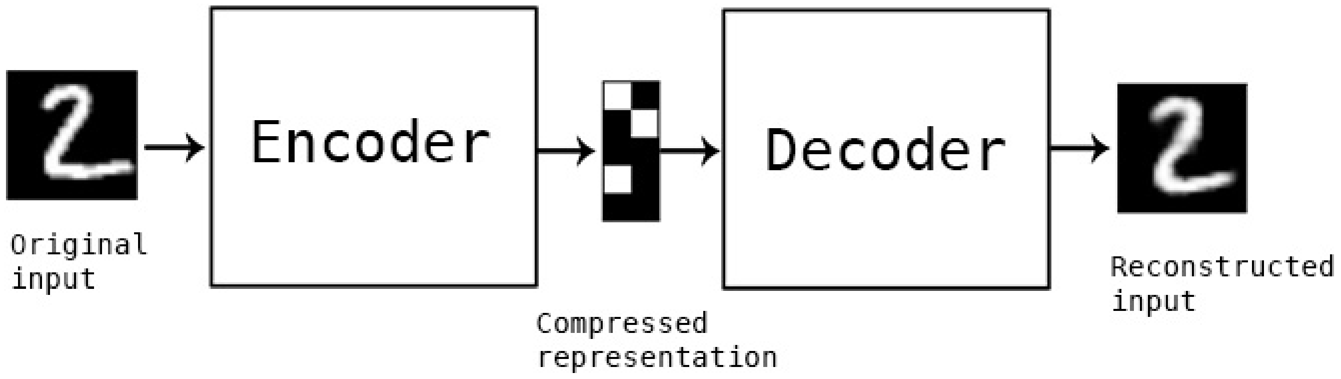
When training CNNs, one of the problems is that we need a lot of labeled data. In the case of image classification, we need to separate images into different classes, which is a manual effort.

## Pre-lecture quiz

However, we might want to use raw (unlabeled) data for training CNN feature extractors, which is called **self-supervised learning**. Instead of labels, we will use training images as both network input and output. The main idea of **autoencoder** is that we will have an **encoder network** that converts input image into some **latent space** (normally it is just a vector of some smaller size), then the **decoder network**, whose goal would be to reconstruct the original image.

> ✅ An autoencoder is "a type of artificial neural network used to learn efficient codings of unlabeled data."

Since we are training an autoencoder to capture as much of the information from the original image as possible for accurate reconstruction, the network tries to find the best **embedding** of input images to capture the meaning.л.



> Image from Keras blog

## Scenarios for using Autoencoders

While reconstructing original images does not seem useful in its own right, there are a few scenarios where autoencoders are especially useful:

- **Lowering the dimension of images for visualization** or **training image embeddings**. Usually autoencoders give better results than PCA, because it takes into account spatial nature of images and hierarchical features.
- **Denoising**, i.e. removing noise from the image. Because noise carries out a lot of useless information, autoencoder cannot fit it all into relatively small latent space, and thus it captures only important part of the image. When training denoisers, we start with original images, and use images with artificially added noise as input for autoencoder.
- **Super-resolution**, increasing image resolution. We start with high-resolution images, and use the image with lower resolution as the autoencoder input.
- **Generative models**. Once we train the autoencoder, the decoder part can be used to create new objects starting from random latent vectors.

# Variational Autoencoders (VAE)

Traditional autoencoders reduce the dimension of the input data somehow, figuring out the important features of input images. However, latent vectors ofter do not make much sense. In other words, taking MNIST dataset as an example, figuring out which digits correspond to different latent vectors is not an easy task, because close latent vectors would not necessarily correspond to the same digits.

On the other hand, to train *generative* models it is better to have some understanding of the latent space. This idea leads us to **variational auto-encoder** (VAE).

VAE is the autoencoder that learns to predict *statistical distribution* of the latent parameters, so-called **latent distribution**. For example, we may want latent vectors to be distributed normally with some mean $z_{mean}$ and standard deviation $z_{sigma}$ (both mean and standard deviation are vectors of some dimensionality d). Encoder in VAE learns to predict those parameters, and then decoder takes a random vector from this distribution to reconstruct the object.

To summarize:

- From input vector, we predict `z_mean` and `z_log_sigma` (instead of predicting the standard deviation itself, we predict its logarithm)
- We sample a vector `sample` from the distribution $N(z_{mean},exp(z_{log\_sigma}))$
- The decoder tries to decode the original image using `sample` as an input vector

> Image from this blog post by Isaak Dykeman

Variational auto-encoders use a complex loss function that consists of two parts:

- **Reconstruction loss** is the loss function that shows how close a reconstructed image is to the target (it can be Mean Squared Error, or MSE). It is the same loss function as in normal autoencoders.
- **KL loss**, which ensures that latent variable distributions stays close to normal distribution. It is based on the notion of Kullback-Leibler divergence - a metric to estimate how similar two statistical distributions are.

One important advantage of VAEs is that they allow us to generate new images relatively easily, because we know which distribution from which to sample latent vectors. For example, if we train

VAE with 2D latent vector on MNIST, we can then vary components of the latent vector to get different digits:

vaemnist

> Image by Dmitry Soshnikov

Observe how images blend into each other, as we start getting latent vectors from the different portions of the latent parameter space. We can also visualize this space in 2D:

vaemnist cluster

> Image by Dmitry Soshnikov

## ✍️ Exercises: Autoencoders

Learn more about autoencoders in these corresponding notebooks:

- Autoencoders in TensorFlow
- Autoencoders in PyTorch

## Properties of Autoencoders

- **Data Specific** - they only work well with the type of images they have been trained on. For example, if we train a super-resolution network on flowers, it will not work well on portraits. This is because the network can produce higher resolution image by taking fine details from features learned from the training dataset.
- **Lossy** - the reconstructed image is not the same as the original image. The nature of loss is defined by the *loss function* used during training
- Works on **unlabeled data**

## Post-lecture quiz

## Conclusion

In this lesson, you learned about the various types of autoencoders available to the AI scientist. You learned how to build them, and how to use them to reconstruct images. You also learned about the VAE and how to use it to generate new images.

## 🚀 Challenge

In this lesson, you learned about using autoencoders for images. But they can also be used for music! Check out the Magenta project's MusicVAE project, which uses autoencoders to learn to reconstruct music. Do some experiments with this library to see what you can create.

## Post-lecture quiz

## Review & Self Study

For reference, read more about autoencoders in these resources:

- Building Autoencoders in Keras
- Blog post on NeuroHive
- Variational Autoencoders Explained
- Conditional Variational Autoencoders

## Assignment

At the end of this notebook using TensorFlow, you will find a 'task' - use this as your assignment.

# Generative Adversarial Networks

In the previous section, we learned about **generative models**: models that can generate new images similar to the ones in the training dataset. VAE was a good example of a generative model.

## Pre-lecture quiz

However, if we try to generate something really meaningful, like a painting at reasonable resolution, with VAE, we will see that training does not converge well. For this use case, we should learn about another architecture specifically targeted at generative models - **Generative Adversarial Networks**, or GANs.

The main idea of a GAN is to have two neural networks that will be trained against each other:

> Image by Dmitry Soshnikov

> ✅ A little vocabulary:
>
> - **Generator** is a network that takes some random vector, and produces the image as a result
> - **Discriminator** is a network that takes an image, and it should tell whether it is a real image (from training dataset), or it was generated by a generator. It is essentially an image classifier.

### Discriminator

The architecture of discriminator does not differ from an ordinary image classification network. In the simplest case it can be fully-connected classifier, but most probably it will be a convolutional network.

> ✅ A GAN based on convolutional networks is called a DCGAN

A CNN discriminator consists of the following layers: several convolutions+poolings (with decreasing spatial size) and, one-or-more fully-connected layers to get "feature vector", final binary classifier.

> ✅ A 'pooling' in this context is a technique that reduces the size of the image. "Pooling layers reduce the dimensions of data by combining the outputs of neuron clusters at one layer into a

> single neuron in the next layer." - source

## Generator

A Generator is slightly more tricky. You can consider it to be a reversed discriminator. Starting from a latent vector (in place of a feature vector), it has a fully-connected layer to convert it into the required size/shape, followed by deconvolutions+upscaling. This is similar to *decoder* part of autoencoder.

> ✅ Because the convolution layer is implemented as a linear filter traversing the image, deconvolution is essentially similar to convolution, and can be implemented using the same layer logic.

> Image by Dmitry Soshnikov

## Training the GAN

GANs are called **adversarial** because there is a constant competition between the generator and the discriminator. During this competition, both generator and discriminator improve, thus the network learns to produce better and better pictures.

The training happens in two stages:

- **Training the discriminator**. This task is pretty straightforward: we generate a batch of images by the generator, labeling them 0, which stands for fake image, and taking a batch of images from the input dataset (with label 1, real image). We obtain some *discriminator loss*, and perform backprop.
- **Training the generator**. This is slightly more tricky, because we do not know the expected output for the generator directly. We take the whole GAN network consisting of a generator followed by discriminator, feed it with some random vectors, and expect the result to be 1 (corresponding to real images). We then freeze the parameters of the discriminator (we do not want it to be trained at this step), and perform the backprop.

During this process, both the generator and the discriminator losses are not going down significantly. In the ideal situation, they should oscillate, corresponding to both networks improving their performance.

## ✍️ Exercises: GANs

- GAN Notebook in TensorFlow/Keras
- GAN Notebook in PyTorch

### Problems with GAN training

GANs are known to be especially difficult to train. Here are a few problems:

- **Mode Collapse**. By this term we mean that the generator learns to produce one successful image that tricks the generator, and not a variety of different images.
- **Sensitivity to hyperparameters**. Often you can see that a GAN does not converge at all, and then suddenly decreases in the learning rate leading to convergence.
- Keeping a **balance** between the generator and the discriminator. In many cases discriminator loss can drop to zero relatively quickly, which results in the generator being unable to train further. To overcome this, we can try setting different learning rates for the generator and discriminator, or skip discriminator training if the loss is already too low.
- Training for **high resolution**. Reflecting the same problem as with autoencoders, this problem is triggered because reconstructing too many layers of convolutional network leads to artifacts. This problem is typically solved with so-called **progressive growing**, when first a few layers are trained on low-res images, and then layers are "unblocked" or added. Another solution would be adding extra connections between layers and training several resolutions at once - see this Multi-Scale Gradient GANs paper for details.

## Style Transfer

GANs is a great way to generate artistic images. Another interesting technique is so-called **style transfer**, which takes one **content image**, and re-draws it in a different style, applying filters from **style image**.

The way it works is the following:

- We start with a random noise image (or with a content image, but for the sake of understanding it is easier to start from random noise)
- Our goal would be to create such an image, that would be close to both content image and style image. This would be determined by two loss functions:

    - **Content loss** is computed based on the features extracted by the CNN at some layers from current image and content image
    - **Style loss** is computed between current image and style image in a clever way using Gram matrices (more details in the example notebook)
- To make the image smoother and remove noise, we also introduce **Variation loss**, which computes average distance between neighboring pixels
- The main optimization loop adjusts current image using gradient descent (or some other optimization algorithm) to minimize the total loss, which is a weighted sum of all three losses.

## ✍️ Example:Style Transfer

## Post-lecture quiz

## Conclusion

In this lesson, you learned about GANS and how to train them. You also learned about the special challenges that this type of Neural Network can face, and some strategies on how to move past them.

## 🚀 Challenge

Run through the Style Transfer notebook using your own images.

## Review & Self Study

For reference, read more about GANs in these resources:

- Marco Pasini, 10 Lessons I Learned Training GANs for one Year
- StyleGAN, a *de facto* GAN architecture to consider
- Creating Generative Art using GANs on Azure ML

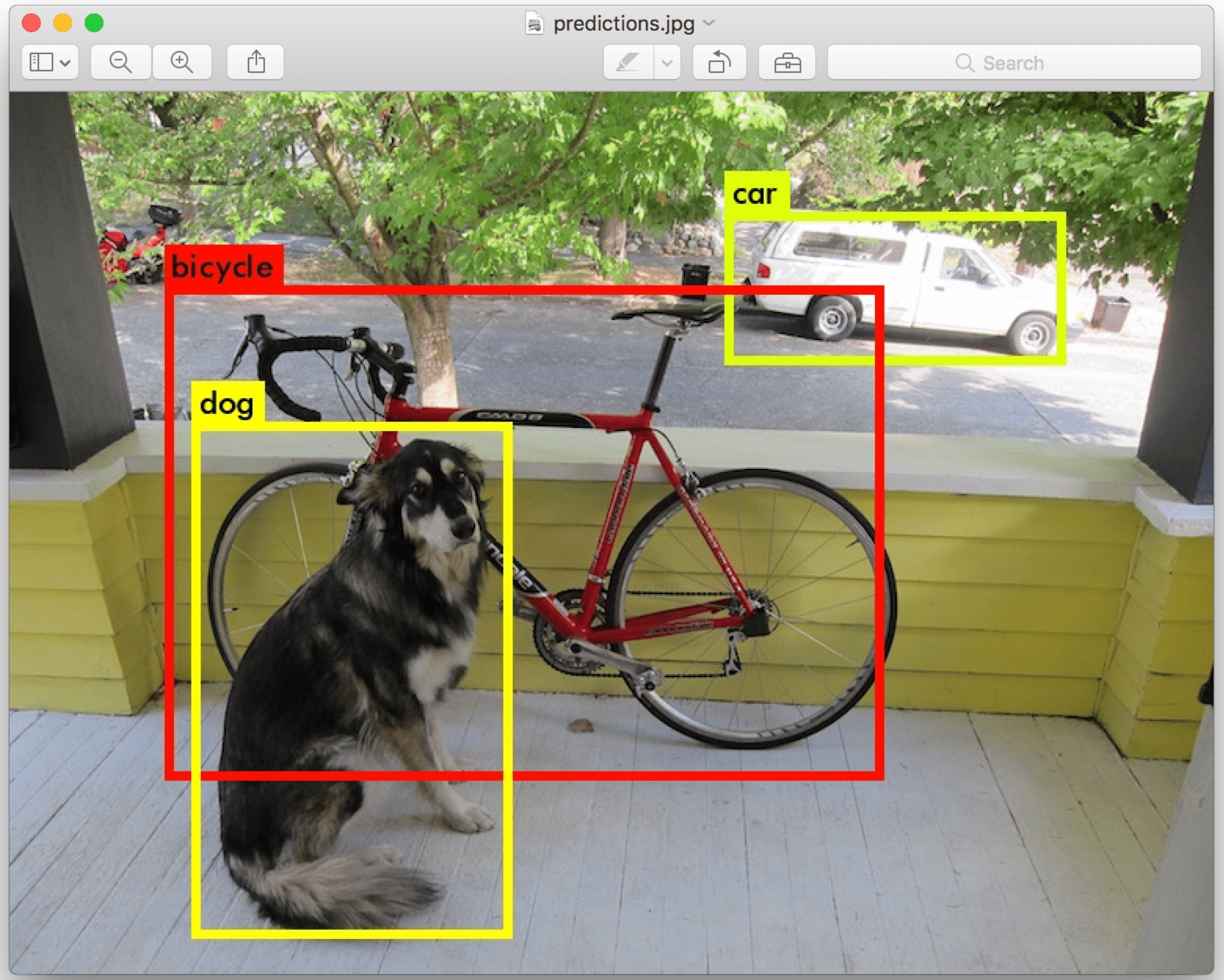
## Assignment

Revisit one of the two notebooks associated to this lesson and retrain the GAN on your own images. What can you create?

# Object Detection

The image classification models we have dealt with so far took an image and produced a categorical result, such as the class 'number' in a MNIST problem. However, in many cases we do not want just to know that a picture portrays objects - we want to be able to determine their precise location. This is exactly the point of **object detection**.

## Pre-lecture quiz

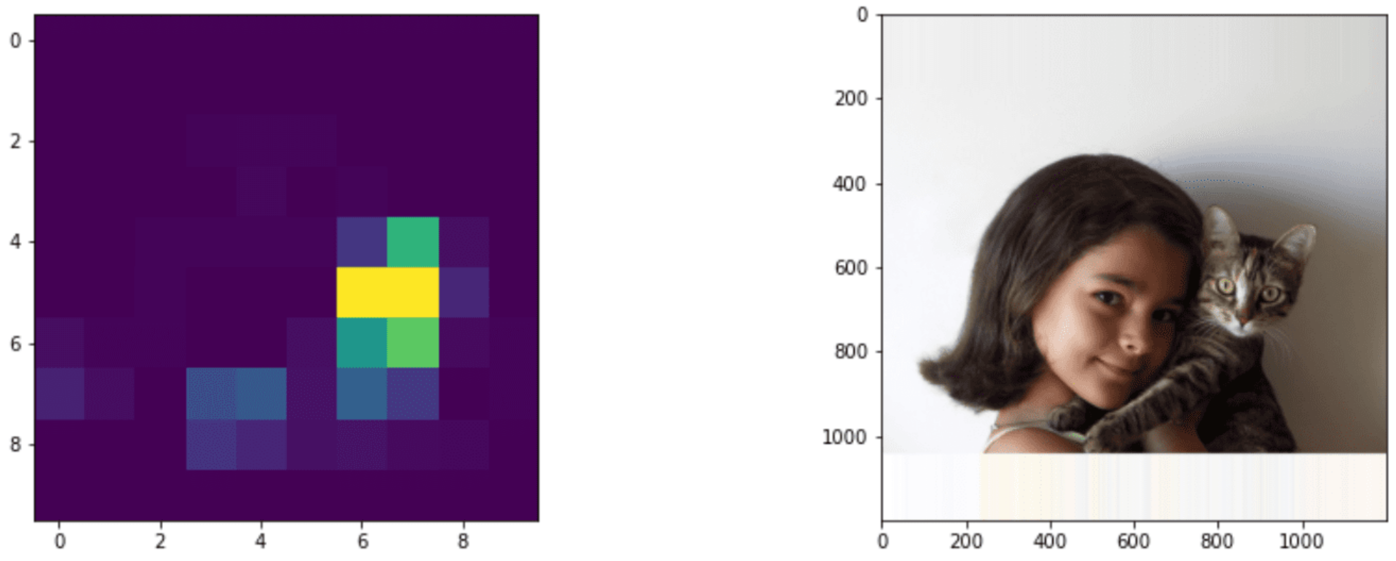


> Image from YOLO v2 web site

## A Naive Approach to Object Detection

Assuming we wanted to find a cat on a picture, a very naive approach to object detection would be the following:

1. Break the picture down to a number of tiles
2. Run image classification on each tile.
3. Those tiles that result in sufficiently high activation can be considered to contain the object in question.



> Image from Exercise Notebook

However, this approach is far from ideal, because it only allows the algorithm to locate the object's bounding box very imprecisely. For more precise location, we need to run some sort of **regression** to predict the coordinates of bounding boxes - and for that, we need specific datasets.

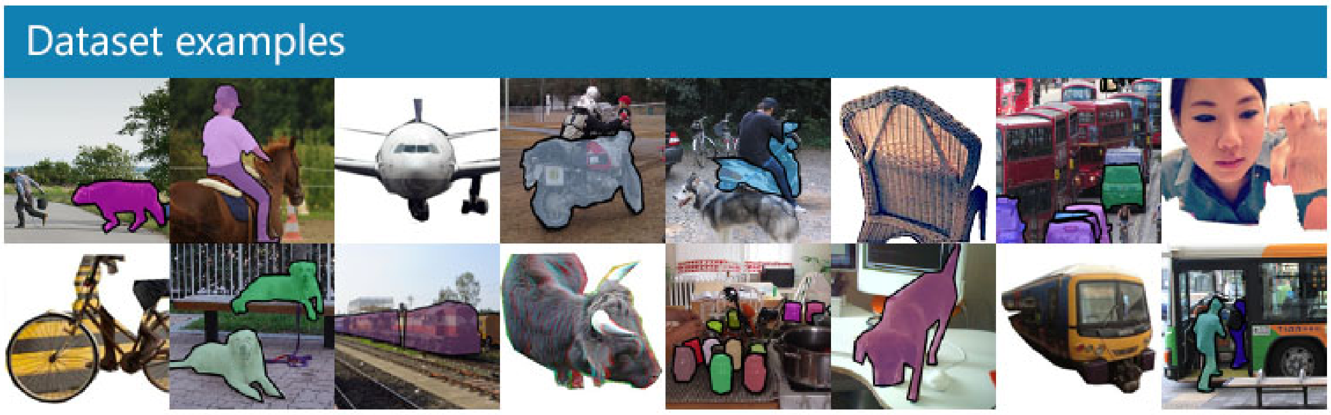
## Regression for Object Detection

This blog post has a great gentle introduction to detecting shapes.

## Datasets for Object Detection

You might run across the following datasets for this task:

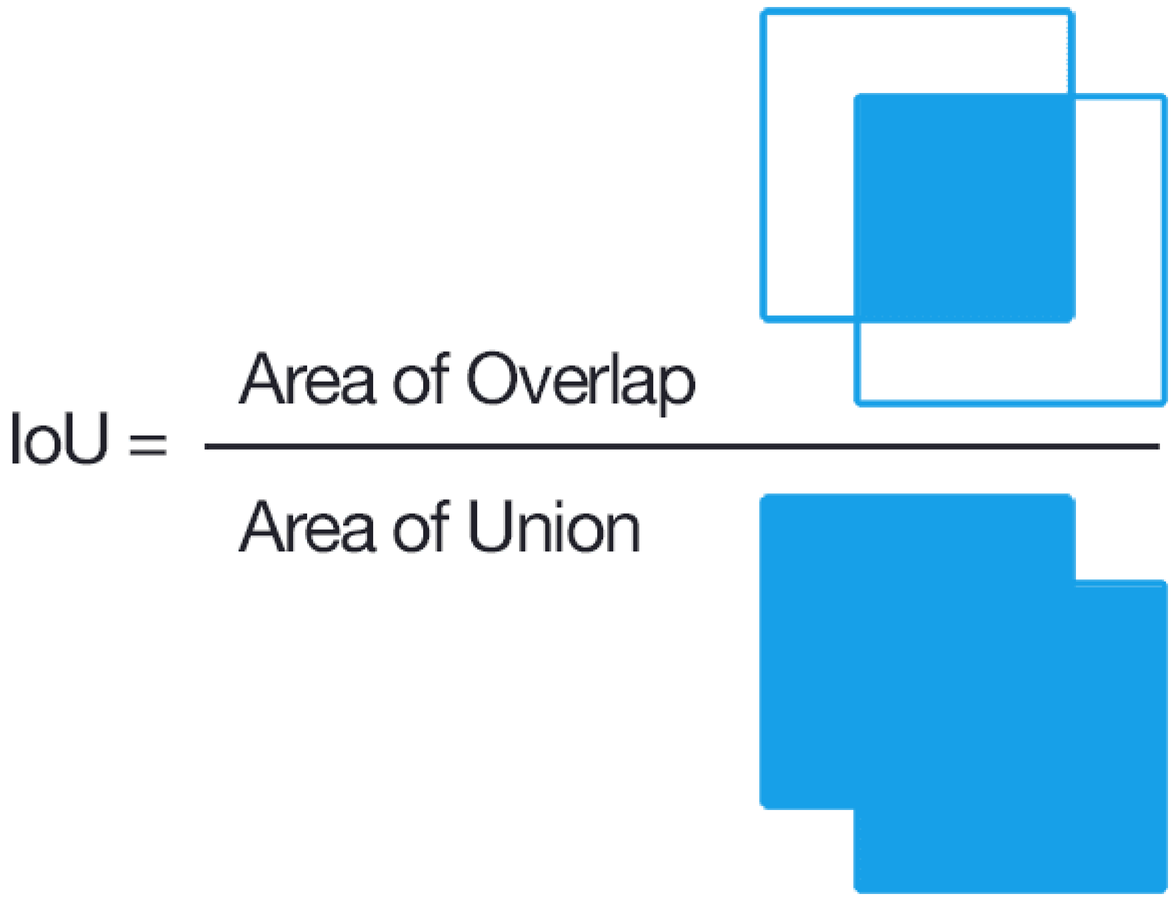
- PASCAL VOC - 20 classes
- COCO - Common Objects in Context. 80 classes, bounding boxes and segmentation masks



## Object Detection Metrics

### Intersection over Union

While for image classification it is easy to measure how well the algorithm performs, for object detection we need to measure both the correctness of the class, as well as the precision of the inferred bounding box location. For the latter, we use the so-called **Intersection over Union** (IoU), which measures how well two boxes (or two arbitrary areas) overlap.



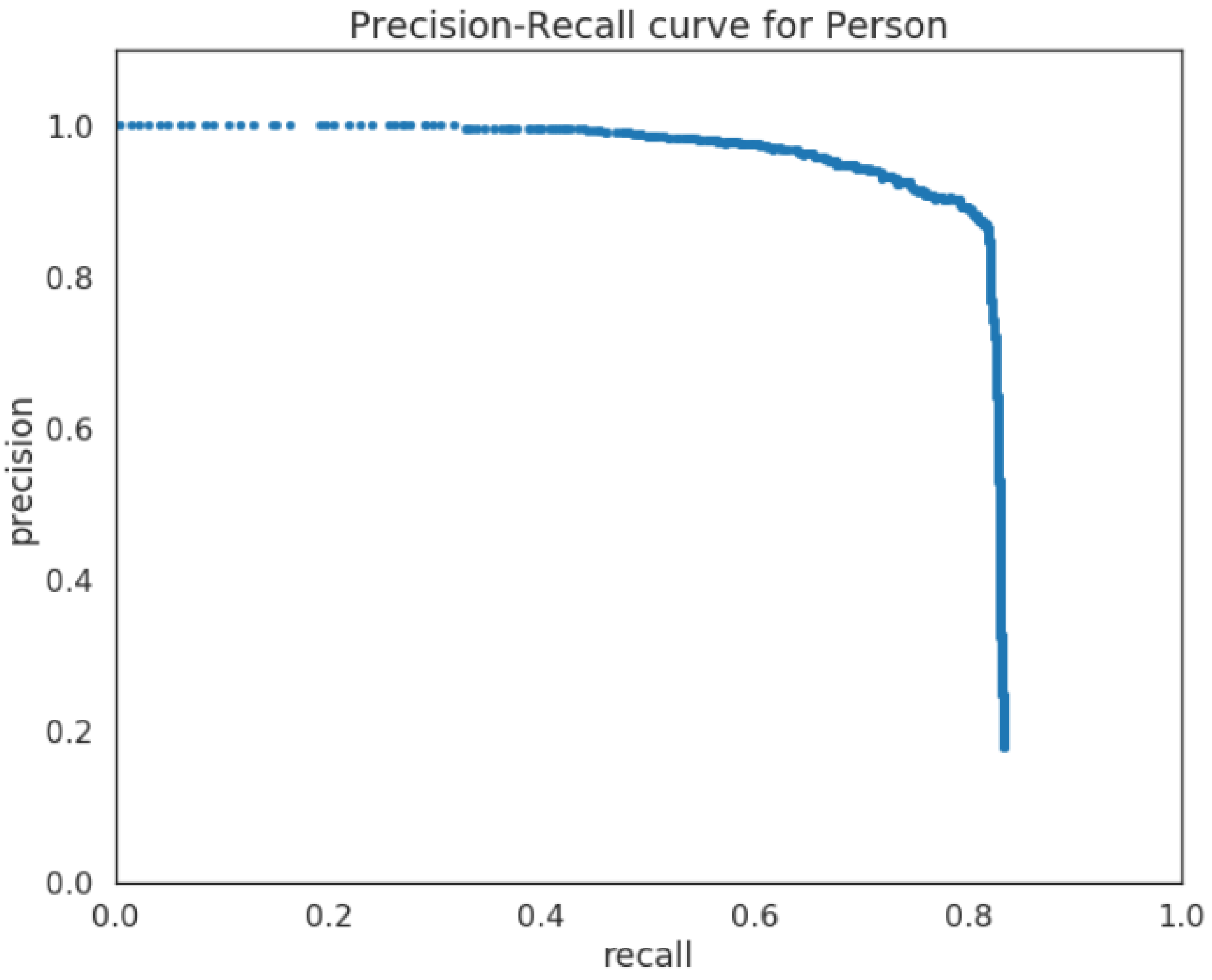
> Figure 2 from this excellent blog post on IoU

The idea is simple - we divide the area of intersection between two figures by the area of their union. For two identical areas, IoU would be 1, while for completely disjointed areas it will be 0. Otherwise it will vary from 0 to 1. We typically only consider those bounding boxes for which IoU is over a certain value.

## Average Precision

Suppose we want to measure how well a given class of objects $C$ is recognized. To measure it, we use **Average Precision** metrics, which is calculated as follows:

1. Consider Precision-Recall curve shows the accuracy depending on a detection threshold value (from 0 to 1).
2. Depending on the threshold, we will get more or less objects detected in the image, and different values of precision and recall.
3. The curve will look like this:



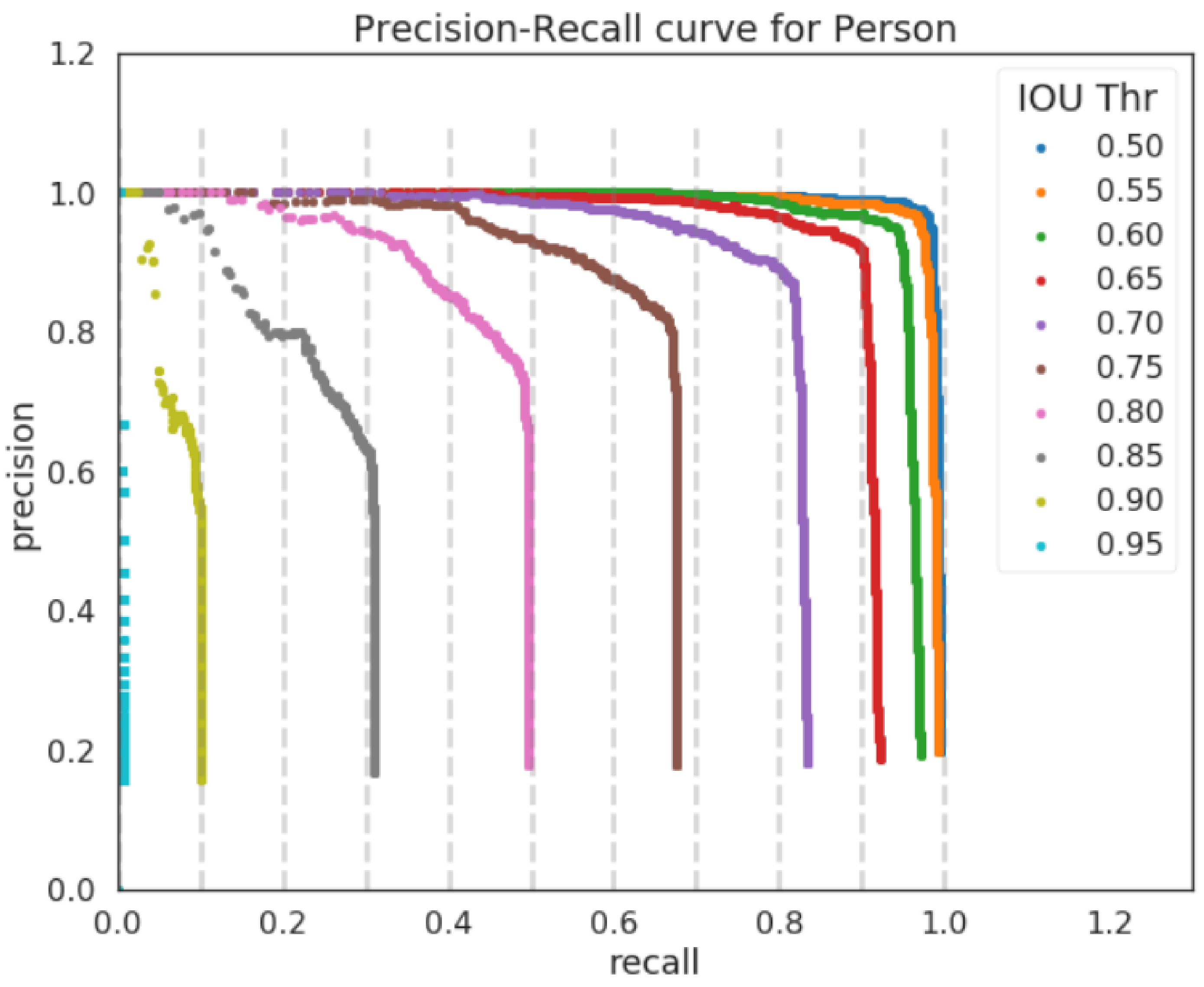
> Image from NeuroWorkshop

The average Precision for a given class $C$ is the area under this curve. More precisely, Recall axis is typically divided into 10 parts, and Precision is averaged over all those points:

$$ AP = {1\over11}\sum_{i=0}^{10}\mbox{Precision}(\mbox{Recall}={i\over10}) $$

## AP and IoU

We shall consider only those detections, for which IoU is above a certain value. For example, in PASCAL VOC dataset typically $\mbox{IoU Threshold} = 0.5$ is assumed, while in COCO AP is measured for different values of $\mbox{IoU Threshold}$.



> Image from NeuroWorkshop

### Mean Average Precision - mAP

The main metric for Object Detection is called **Mean Average Precision**, or **mAP**. It is the value of Average Precision, average across all object classes, and sometimes also over $\mbox{IoU Threshold}$. In more detail, the process of calculating **mAP** is described in this blog post), and also here with code samples.

## Different Object Detection Approaches

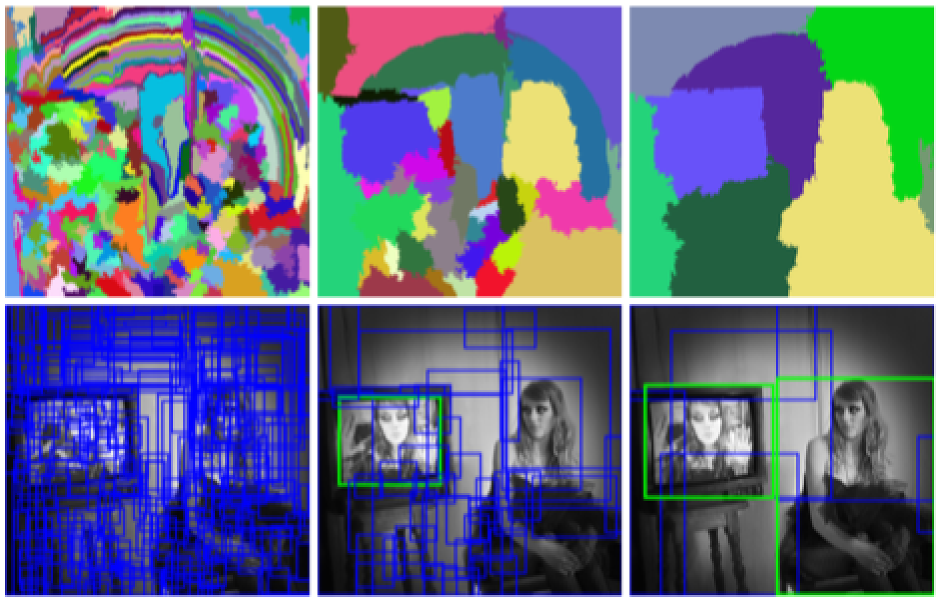
There are two broad classes of object detection algorithms:

- **Region Proposal Networks** (R-CNN, Fast R-CNN, Faster R-CNN). The main idea is to generate **Regions of Interests** (ROI) and run CNN over them, looking for maximum activation. It is a bit similar to the naive approach, with the exception that ROIs are generated in a more clever way. One of the majors drawbacks of such methods is that they are slow, because we need many passes of the CNN classifier over the image.

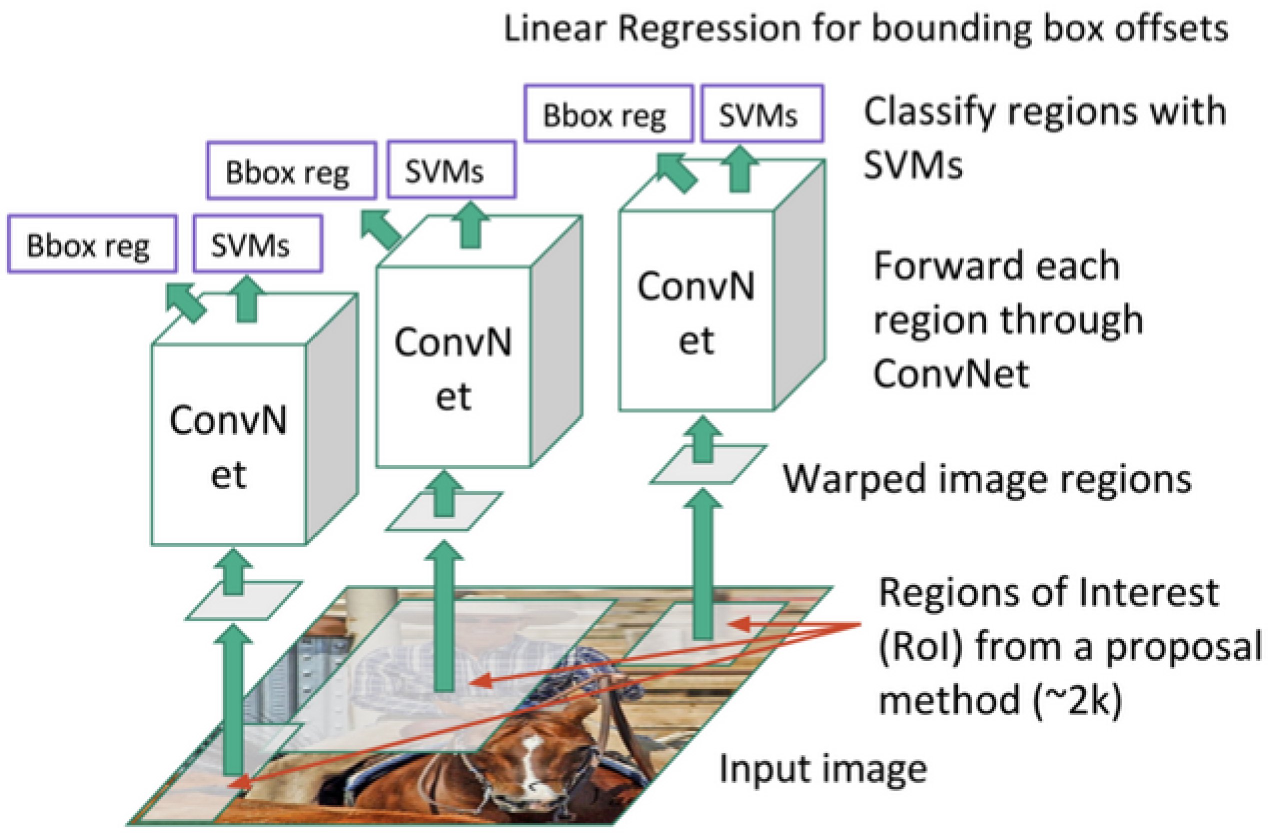
- **One-pass** (YOLO, SSD, RetinaNet) methods. In those architectures we design the network to predict both classes and ROIs in one pass.

## R-CNN: Region-Based CNN

R-CNN uses Selective Search to generate hierarchical structure of ROI regions, which are then passed through CNN feature extractors and SVM-classifiers to determine the object class, and linear regression to determine *bounding box* coordinates. Official Paper



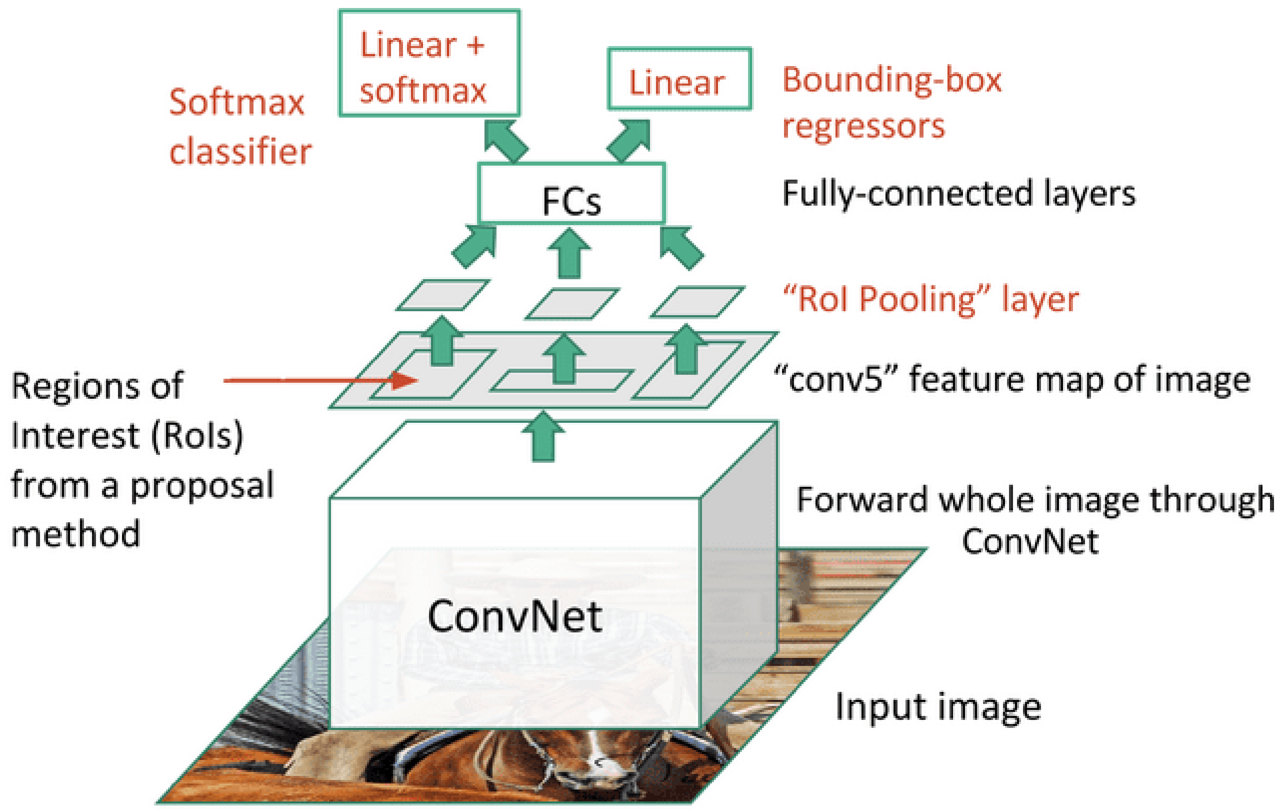
> Image from van de Sande et al. ICCV'11


Linear Regression for bounding box offsets
Bbox reg
SVMs
Bbox reg
SVMs
Bbox reg
SVMs
Classify regions with SVMs
ConvNet
ConvNet
ConvNet
Forward each region through ConvNet
Warped image regions
Regions of Interest (RoI) from a proposal method (~2k)
Input image

> *Images from this blog

## F-RCNN - Fast R-CNN

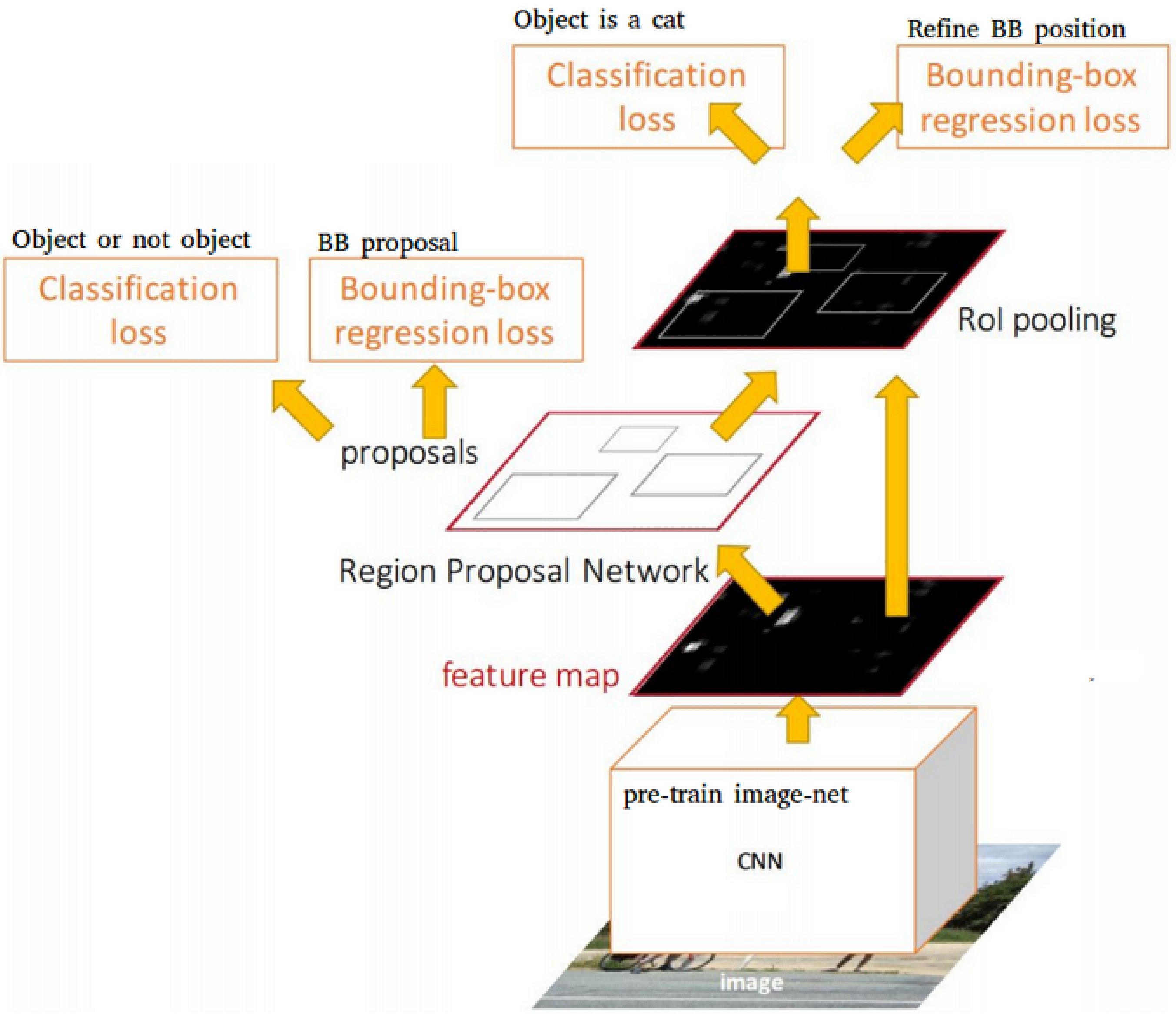
This approach is similar to R-CNN, but regions are defined after convolution layers have been applied.



> Image from the Official Paper, arXiv, 2015

## Faster R-CNN

The main idea of this approach is to use neural network to predict ROIs - so-called *Region Proposal Network*. Paper, 2016



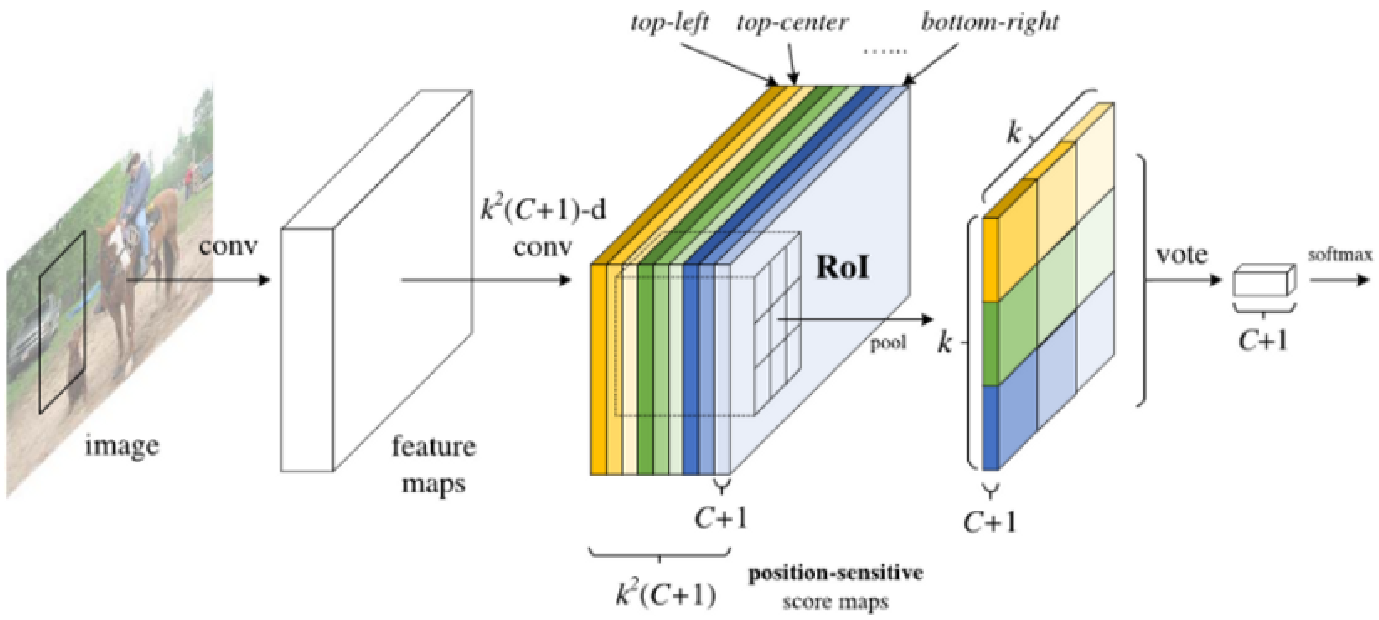
> Image from the official paper

## R-FCN: Region-Based Fully Convolutional Network

This algorithm is even faster than Faster R-CNN. The main idea is the following:

1. We extract features using ResNet-101

2. Features are processed by **Position-Sensitive Score Map**. Each object from $C$ classes is divided by $k\times k$ regions, and we are training to predict parts of objects.
3. For each part from $k\times k$ regions all networks vote for object classes, and the object class with maximum vote is selected.

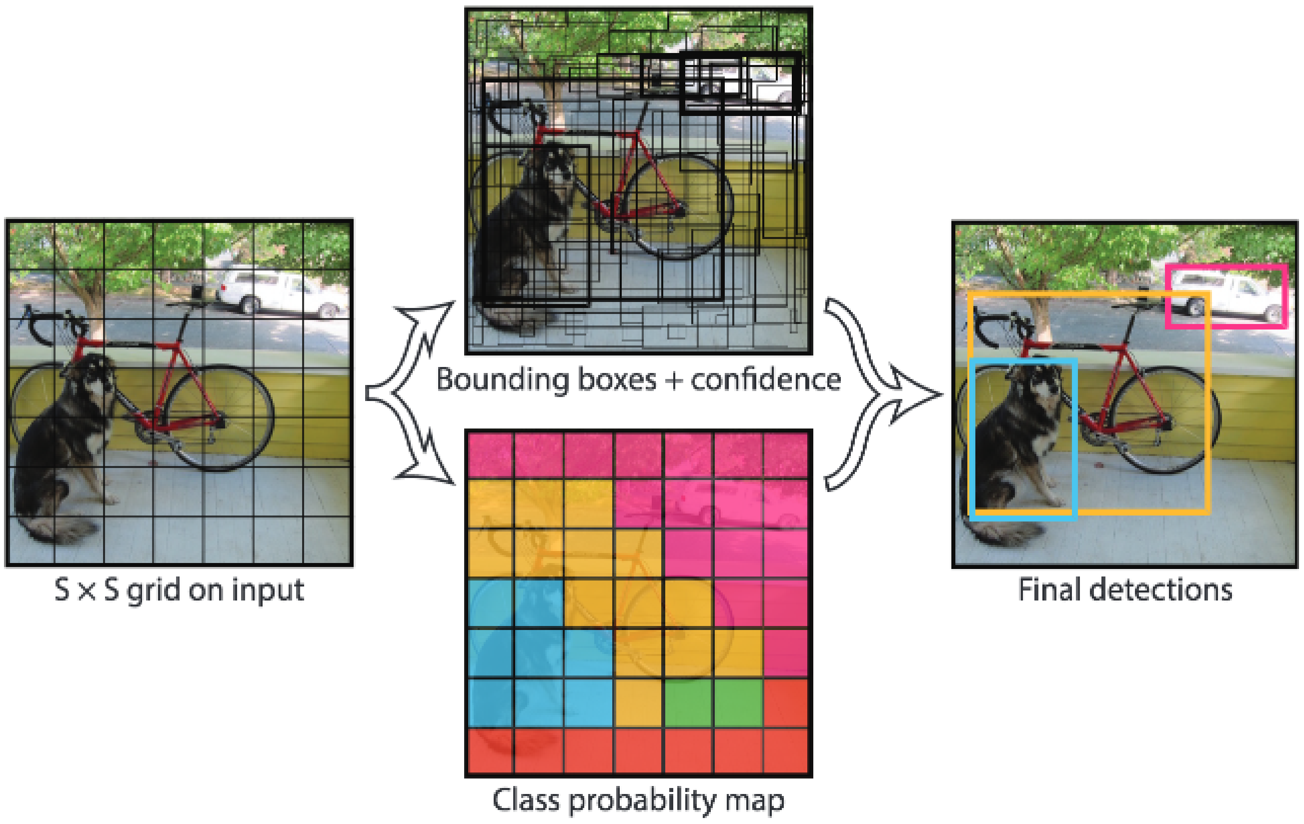


> Image from official paper

## YOLO - You Only Look Once

YOLO is a realtime one-pass algorithm. The main idea is the following:

- Image is divided into $S\times S$ regions
- For each region, **CNN** predicts $n$ possible objects, *bounding box* coordinates and *confidence=probability* * IoU.



> Image from official paper

### Other Algorithms

- RetinaNet: official paper
    - PyTorch Implementation in Torchvision
    - Keras Implementation
    - Object Detection with RetinaNet in Keras Samples
- SSD (Single Shot Detector): official paper

## ✍️ Exercises: Object Detection

Continue your learning in the following notebook:

ObjectDetection.ipynb

## Conclusion

In this lesson you took a whirlwind tour of all the various ways that object detection can be accomplished!

## 🚀 Challenge

Read through these articles and notebooks about YOLO and try them for yourself

- Good blog post describing YOLO
- Official site
- Yolo: Keras implementation, step-by-step notebook
- Yolo v2: Keras implementation, step-by-step notebook

## Post-lecture quiz

## Review & Self Study

- Object Detection by Nikhil Sardana
- A good comparison of object detection algorithms
- Review of Deep Learning Algorithms for Object Detection
- A Step-by-Step Introduction to the Basic Object Detection Algorithms
- Implementation of Faster R-CNN in Python for Object Detection

## Assignment: Object Detection

# Segmentation

We have previously learned about Object Detection, which allows us to locate objects in the image by predicting their *bounding boxes*. However, for some tasks we do not only need bounding boxes, but also more precise object localization. This task is called **segmentation**.

## Pre-lecture quiz

Segmentation can be viewed as **pixel classification**, whereas for **each** pixel of image we must predict its class (*background* being one of the classes). There are two main segmentation algorithms:

- **Semantic segmentation** only tells the pixel class, and does not make a distinction between different objects of the same class
- **Instance segmentation** divides classes into different instances.

For instance segmentation, these sheep are different objects, but for semantic segmentation all sheep are represented by one class.

> Image from this blog post

There are different neural architectures for segmentation, but they all have the same structure. In a way, it is similar to the autoencoder you learned about previously, but instead of deconstructing the original image, our goal is to deconstruct a **mask**. Thus, a segmentation network has the following parts:

- **Encoder** extracts features from input image
- **Decoder** transforms those features into the **mask image**, with the same size and number of channels corresponding to the number of classes.

> Image from this publication

We should especially mention the loss function that is used for segmentation. When using classical autoencoders, we need to measure the similarity between two images, and we can use mean square error (MSE) to do that. In segmentation, each pixel in the target mask image represents the class number (one-hot-encoded along the third dimension), so we need to use loss functions specific for classification - cross-entropy loss, averaged over all pixels. If the mask is binary - **binary cross-entropy loss** (BCE) is used.

> ✅ One-hot encoding is a way to encode a class label into a vector of length equal to the number of classes. Take a look at this article on this technique.

## Segmentation for Medical Imaging

In this lesson, we will see the segmentation in action by training the network to recognize human nevi (also known as moles) on medical images. We will be using PH$^2$ Database of dermoscopy images as the image source. This dataset contains 200 images of three classes: typical nevus, atypical nevus, and melanoma. All images also contain a corresponding **mask** that outlines the nevus.

> ✅ This technique is particularly appropriate for this type of medical imaging, but what other real-world applications could you envision?

navi

> Image from the PH$^2$ Database

We will train a model to segment any nevus from its background.

## ✍️ Exercises: Semantic Segmentation

Open the notebooks below to learn more about different semantic segmentation architectures, practice working with them, and see them in action.

- Semantic Segmentation Pytorch
- Semantic Segmentation TensorFlow

## Post-lecture quiz

## Conclusion

Segmentation is a very powerful technique for image classification, moving beyond bounding boxes to pixel-level classification. It is a technique used in medical imaging, among other applications.

## 🚀 Challenge

Body segmentation is just one of the common tasks that we can do with images of people. Another important tasks include **skeleton detection** and **pose detection**. Try out OpenPose library to see how pose detection can be used.

## Review & Self Study

This wikipedia article offers a good overview of the various applications of this technique. Learn more on your own about the subdomains of Instance segmentation and Panoptic segmentation in this field of inquiry.

## Assignment

In this lab, try **human body segmentation** using Segmentation Full Body MADS Dataset from Kaggle.

# Representing Text as Tensors

## Pre-lecture quiz

## Text Classification

Throughout the first part of this section, we will focus on **text classification** task. We will use the AG News Dataset, which contains news articles like the following:

- Category: Sci/Tech
- Title: Ky. Company Wins Grant to Study Peptides (AP)
- Body: AP - A company founded by a chemistry researcher at the University of Louisville won a grant to develop...

Our goal will be to classify the news item into one of the categories based on text.

## Representing text

If we want to solve Natural Language Processing (NLP) tasks with neural networks, we need some way to represent text as tensors. Computers already represent textual characters as numbers that map to fonts on your screen using encodings such as ASCII or UTF-8.

Image showing diagram mapping a character to an ASCII and binary representation

> Image source

As humans, we understand what each letter **represents**, and how all characters come together to form the words of a sentence. However, computers by themselves do not have such an understanding, and neural network has to learn the meaning during training.

Therefore, we can use different approaches when representing text:

- **Character-level representation**, when we represent text by treating each character as a number. Given that we have *C* different characters in our text corpus, the word *Hello* would be represented by 5x*C* tensor. Each letter would correspond to a tensor column in one-hot encoding.
- **Word-level representation**, in which we create a **vocabulary** of all words in our text, and then represent words using one-hot encoding. This approach is somehow better, because each letter by itself does not have much meaning, and thus by using higher-level semantic concepts - words - we simplify the task for the neural network. However, given the large dictionary size, we need to deal with high-dimensional sparse tensors.

Regardless of the representation, we first need to convert the text into a sequence of **tokens**, one token being either a character, a word, or sometimes even part of a word. Then, we convert the token into a number, typically using **vocabulary**, and this number can be fed into a neural network using one-hot encoding.

## N-Grams

In natural language, precise meaning of words can only be determined in context. For example, meanings of *neural network* and *fishing network* are completely different. One of the ways to take this into account is to build our model on pairs of words, and considering word pairs as separate vocabulary tokens. In this way, the sentence *I like to go fishing* will be represented by the following sequence of tokens: *I like*, *like to*, *to go*, *go fishing*. The problem with this approach is that the dictionary size grows significantly, and combinations like *go fishing* and *go shopping* are presented by different tokens, which do not share any semantic similarity despite the same verb.

In some cases, we may consider using tri-grams -- combinations of three words -- as well. Thus the approach is such is often called **n-grams**. Also, it makes sense to use n-grams with character-level representation, in which case n-grams will roughly correspond to different syllabi.

## Bag-of-Words and TF/IDF

When solving tasks like text classification, we need to be able to represent text by one fixed-size vector, which we will use as an input to final dense classifier. One of the simplest ways to do that is to combine all individual word representations, eg. by adding them. If we add one-hot encodings of each word, we will end up with a vector of frequencies, showing how many times each word appears inside the text. Such representation of text is called **bag of words** (BoW).

> Image by the author

A BoW essentially represents which words appear in text and in which quantities, which can indeed be a good indication of what the text is about. For example, news article on politics is likely to contains words such as *president* and *country*, while scientific publication would have something like *collider*, *discovered*, etc. Thus, word frequencies can in many cases be a good indicator of text content.

The problem with BoW is that certain common words, such as *and*, *is*, etc. appear in most of the texts, and they have highest frequencies, masking out the words that are really important. We may lower the importance of those words by taking into account the frequency at which words occur in the whole document collection. This is the main idea behind TF/IDF approach, which is covered in more detail in the notebooks attached to this lesson.

However, none of those approaches can fully take into account the **semantics** of text. We need more powerful neural networks models to do this, which we will discuss later in this section.

## ✍️ Exercises: Text Representation

Continue your learning in the following notebooks:

- Text Representation with PyTorch
- Text Representation with TensorFlow

## Conclusion

So far, we have studied techniques that can add frequency weight to different words. They are, however, unable to represent meaning or order. As the famous linguist J. R. Firth said in 1935, "The complete meaning of a word is always contextual, and no study of meaning apart from context can be taken seriously." We will learn later in the course how to capture contextual information from text using language modeling.

## 🚀 Challenge

Try some other exercises using bag-of-words and different data models. You might be inspired by this competition on Kaggle

## Post-lecture quiz

## Review & Self Study

Practice your skills with text embeddings and bag-of-words techniques on Microsoft Learn

## Assignment: Notebooks

# Embeddings

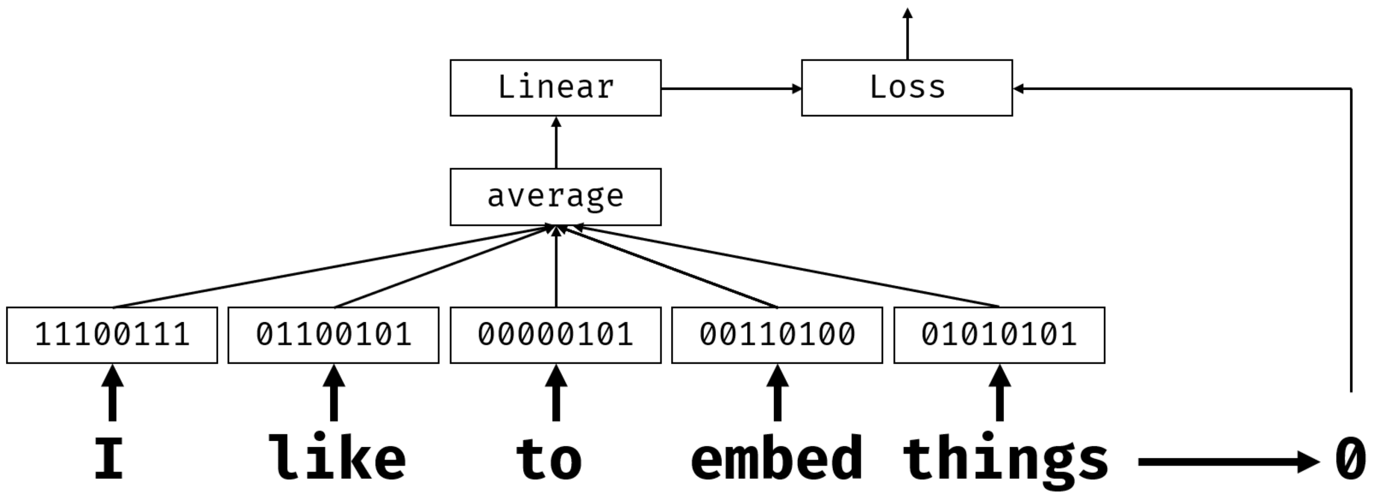
## Pre-lecture quiz

When training classifiers based on BoW or TF/IDF, we operated on high-dimensional bag-of-words vectors with length `vocab_size`, and we were explicitly converting from low-dimensional positional representation vectors into sparse one-hot representation. This one-hot representation, however, is not memory-efficient. In addition, each word is treated independently from each other, i.e. one-hot encoded vectors do not express any semantic similarity between words.

The idea of **embedding** is to represent words by lower-dimensional dense vectors, which somehow reflect the semantic meaning of a word. We will later discuss how to build meaningful word embeddings, but for now let's just think of embeddings as a way to lower dimensionality of a word vector.

So, the embedding layer would take a word as an input, and produce an output vector of specified `embedding_size`. In a sense, it is very similar to a `Linear` layer, but instead of taking a one-hot encoded vector, it will be able to take a word number as an input, allowing us to avoid creating large one-hot-encoded vectors.

By using an embedding layer as a first layer in our classifier network, we can switch from a bag-of-words to **embedding bag** model, where we first convert each word in our text into corresponding embedding, and then compute some aggregate function over all those embeddings, such as `sum`, `average` or `max`.



> Image by the author

## ✍️ Exercises: Embeddings

Continue your learning in the following notebooks:

- Embeddings with PyTorch
- Embeddings TensorFlow

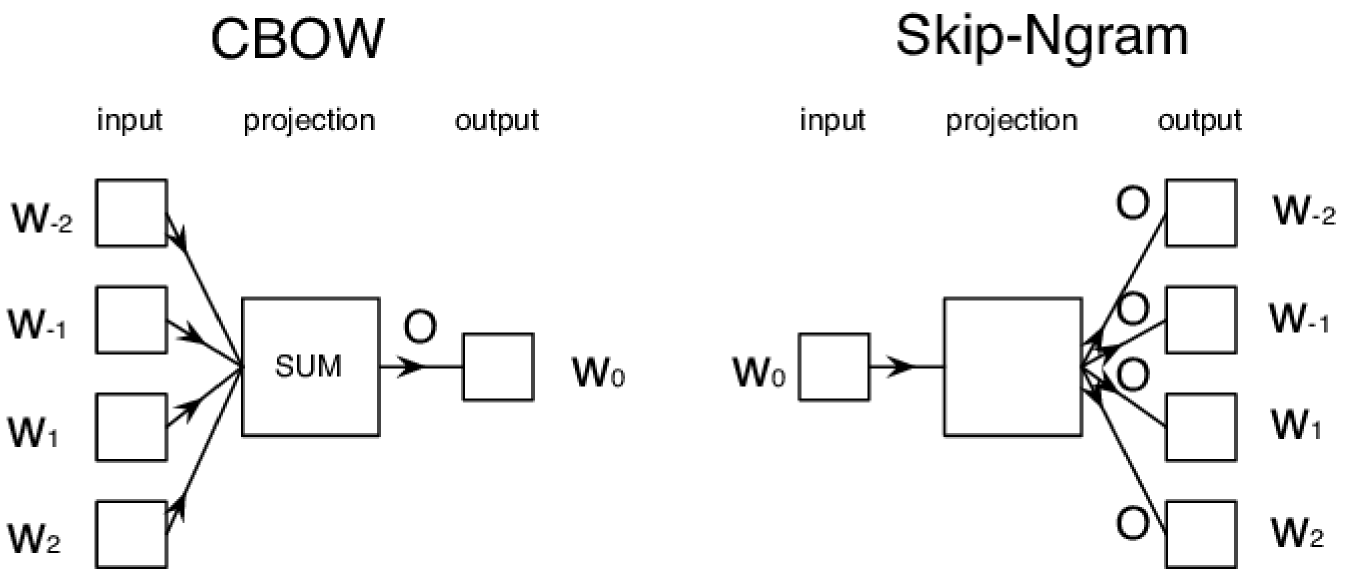
## Semantic Embeddings: Word2Vec

While the embedding layer learned to map words to vector representation, however, this representation did not necessarily have much semantical meaning. It would be nice to learn a vector representation such that similar words or synonyms correspond to vectors that are close to each other in terms of some vector distance (eg. Euclidean distance).

To do that, we need to pre-train our embedding model on a large collection of text in a specific way. One way to train semantic embeddings is called Word2Vec. It is based on two main architectures that are used to produce a distributed representation of words:

- **Continuous bag-of-words** (CBoW) — in this architecture, we train the model to predict a word from surrounding context. Given the ngram $(W_{-2},W_{-1},W_0,W_1,W_2)$, the goal of the model is to predict $W_0$ from $(W_{-2},W_{-1},W_1,W_2)$.
- **Continuous skip-gram** is opposite to CBoW. The model uses surrounding window of context words to predict the current word.

CBoW is faster, while skip-gram is slower, but does a better job of representing infrequent words.



> Image from this paper

Word2Vec pre-trained embeddings (as well as other similar models, such as GloVe) can also be used in place of embedding layer in neural networks. However, we need to deal with vocabularies, because the vocabulary used to pre-train Word2Vec/GloVe is likely to differ from the vocabulary in our text corpus. Have a look into the above Notebooks to see how this problem can be resolved.

## Contextual Embeddings

One key limitation of traditional pretrained embedding representations such as Word2Vec is the problem of word sense disambiguation. While pretrained embeddings can capture some of the meaning of words in context, every possible meaning of a word is encoded into the same embedding. This can cause problems in downstream models, since many words such as the word 'play' have different meanings depending on the context they are used in.

For example word 'play' in those two different sentences have quite different meaning:

- I went to a **play** at the theatre.
- John wants to **play** with his friends.

The pretrained embeddings above represent both of these meanings of the word 'play' in the same embedding. To overcome this limitation, we need to build embeddings based on the **language model**, which is trained on a large corpus of text, and *knows* how words can be put together in different contexts. Discussing contextual embeddings is out of scope for this tutorial, but we will come back to them when talking about language models later in the course.

## Conclusion

In this lesson, you discovered how to build and use embedding layers in TensorFlow and Pytorch to better reflect the semantic meanings of words.

## 🚀 Challenge

Word2Vec has been used for some interesting applications, including generating song lyrics and poetry. Take a look at this article which walks through how the author used Word2Vec to generate poetry. Watch this video by Dan Shiffmann as well to discover a different explanation of this technique. Then try to apply these techniques to your own text corpus, perhaps sourced from Kaggle.

## Post-lecture quiz

## Review & Self Study

Read through this paper on Word2Vec: Efficient Estimation of Word Representations in Vector Space

## Assignment: Notebooks

# Language Modeling

Semantic embeddings, such as Word2Vec and GloVe, are in fact a first step towards **language modeling** - creating models that somehow *understand* (or *represent*) the nature of the language.

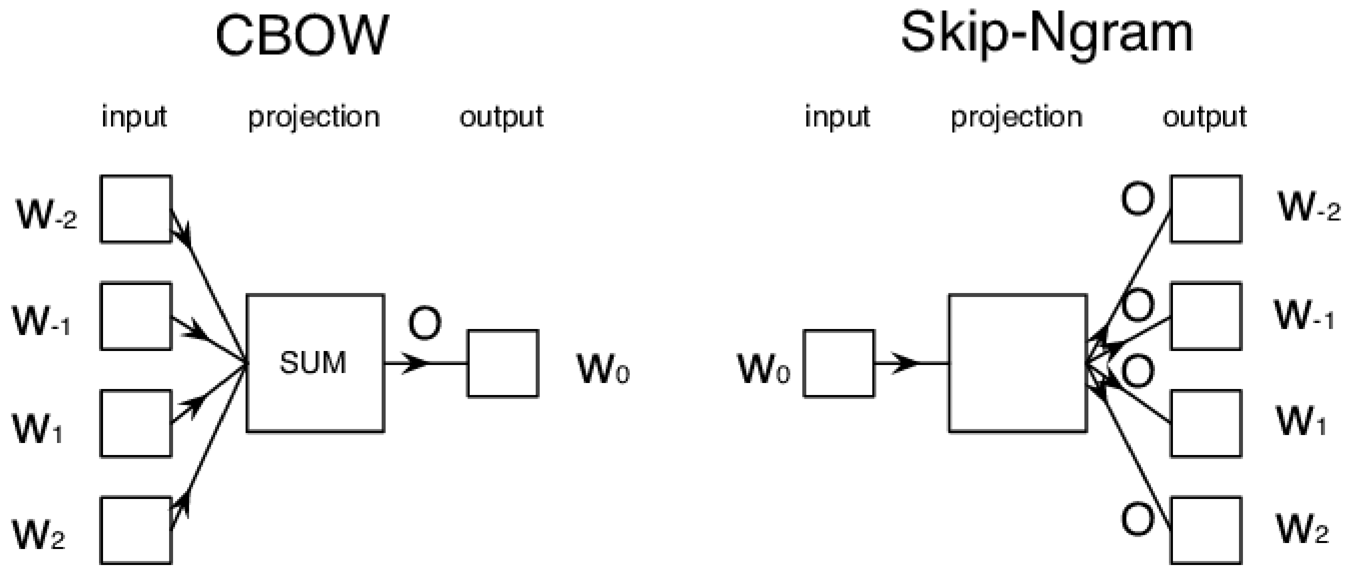
## Pre-lecture quiz

The main idea behind language modeling is training them on unlabeled datasets in an unsupervised manner. This is important because we have huge amounts of unlabeled text available, while the amount of labeled text would always be limited by the amount of effort we can spend on labeling. Most often, we can build language models that can **predict missing words** in the text, because it is easy to mask out a random word in text and use it as a training sample.

## Training Embeddings

In our previous examples, we used pre-trained semantic embeddings, but it is interesting to see how those embeddings can be trained. There are several possible ideas the can be used:

- **N-Gram** language modeling, when we predict a token by looking at N previous tokens (N-gram)
- **Continuous Bag-of-Words** (CBoW), when we predict the middle token $W_0$ in a token sequence $W_{-N}$, ..., $W_N$.
- **Skip-gram**, where we predict a set of neighboring tokens {$W_{-N},\dots, W_{-1}, W_1,\dots, W_N$} from the middle token $W_0$.



> Image from this paper

## ✍️ Example Notebooks: Training CBoW model

Continue your learning in the following notebooks:

- Training CBoW Word2Vec with TensorFlow

## Conclusion

In the previous lesson we have seen that words embeddings work like magic! Now we know that training word embeddings is not a very complex task, and we should be able to train our own word embeddings for domain specific text if needed.

## Post-lecture quiz

## Review & Self Study

- Official PyTorch tutorial on Language Modeling.
- Official TensorFlow tutorial on training Word2Vec model.

- Using the **gensim** framework to train most commonly used embeddings in a few lines of code is described in this documentation.

## 🚀 Assignment: Train Skip-Gram Model

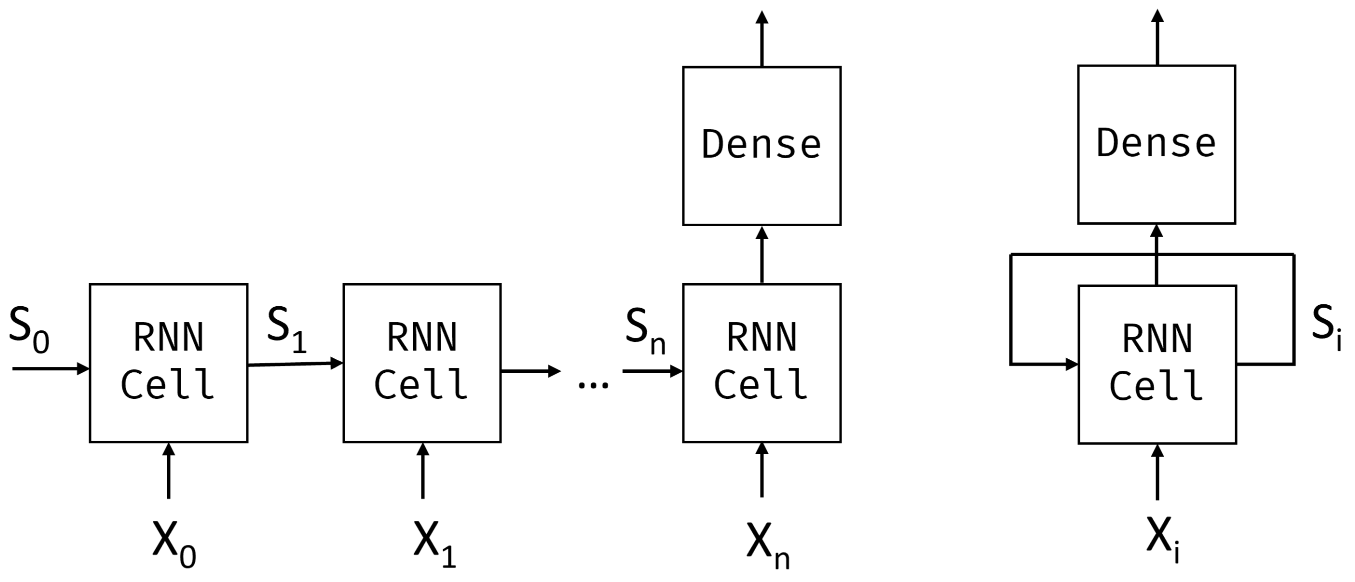
In the lab, we challenge you to modify the code from this lesson to train skip-gram model instead of CBoW. Read the details

## Recurrent Neural Networks

### Pre-lecture quiz

In previous sections, we have been using rich semantic representations of text and a simple linear classifier on top of the embeddings. What this architecture does is to capture the aggregated meaning of words in a sentence, but it does not take into account the **order** of words, because the aggregation operation on top of embeddings removed this information from the original text. Because these models are unable to model word ordering, they cannot solve more complex or ambiguous tasks such as text generation or question answering.

To capture the meaning of text sequence, we need to use another neural network architecture, which is called a **recurrent neural network**, or RNN. In RNN, we pass our sentence through the network one symbol at a time, and the network produces some **state**, which we then pass to the network again with the next symbol.



> Image by the author

Given the input sequence of tokens $X_0,\dots,X_n$, RNN creates a sequence of neural network blocks, and trains this sequence end-to-end using backpropagation. Each network block takes a pair $(X_i,S_i)$ as an input, and produces $S_{i+1}$ as a result. The final state $S_n$ or (output $Y_n$) goes into a linear classifier to produce the result. All the network blocks share the same weights, and are trained end-to-end using one backpropagation pass.

Because state vectors $S_0,\dots,S_n$ are passed through the network, it is able to learn the sequential dependencies between words. For example, when the word *not* appears somewhere in the sequence, it can learn to negate certain elements within the state vector, resulting in negation.

> ✅ Since the weights of all RNN blocks on the picture above are shared, the same picture can be represented as one block (on the right) with a recurrent feedback loop, which passes the output state of the network back to the input.

## Anatomy of an RNN Cell

Let's see how a simple RNN cell is organized. It accepts the previous state $S_{i-1}$ and current symbol $X_i$ as inputs, and has to produce the output state $S_i$ (and, sometimes, we are also interested in some other output $Y_i$, as in the case with generative networks).

A simple RNN cell has two weight matrices inside: one transforms an input symbol (let's call it W), and another one transforms an input state (H). In this case the output of the network is calculated as $\sigma(W\times X_i+H\times S_{i-1}+b)$, where $\sigma$ is the activation function and b is additional bias.

RNN Cell Anatomy

> Image by the author

In many cases, input tokens are passed through the embedding layer before entering the RNN to lower the dimensionality. In this case, if the dimension of the input vectors is *emb_size*, and state vector is *hid_size* - the size of W is *emb_size*×*hid_size*, and the size of H is *hid_size*×*hid_size*.

## Long Short Term Memory (LSTM)

One of the main problems of classical RNNs is the so-called **vanishing gradients** problem. Because RNNs are trained end-to-end in one backpropagation pass, it has difficulty propagating error to the first layers of the network, and thus the network cannot learn relationships between distant tokens. One of the ways to avoid this problem is to introduce **explicit state management** by using so called **gates**. There are two well-known architectures of this kind: **Long Short Term Memory** (LSTM) and **Gated Relay Unit** (GRU).

Image showing an example long short term memory cell

> Image source TBD

The LSTM Network is organized in a manner similar to RNN, but there are two states that are being passed from layer to layer: the actual state C, and the hidden vector H. At each unit, the hidden vector $H_i$ is concatenated with input $X_i$, and they control what happens to the state C via **gates**. Each gate is a neural network with sigmoid activation (output in the range [0,1]), which can be thought of as a bitwise mask when multiplied by the state vector. There are the following gates (from left to right on the picture above):

- The **forget gate** takes a hidden vector and determines which components of the vector C we need to forget, and which to pass through.
- The **input gate** takes some information from the input and hidden vectors and inserts it into state.
- The **output gate** transforms state via a linear layer with *tanh* activation, then selects some of its components using a hidden vector $H_i$ to produce a new state $C_{i+1}$.

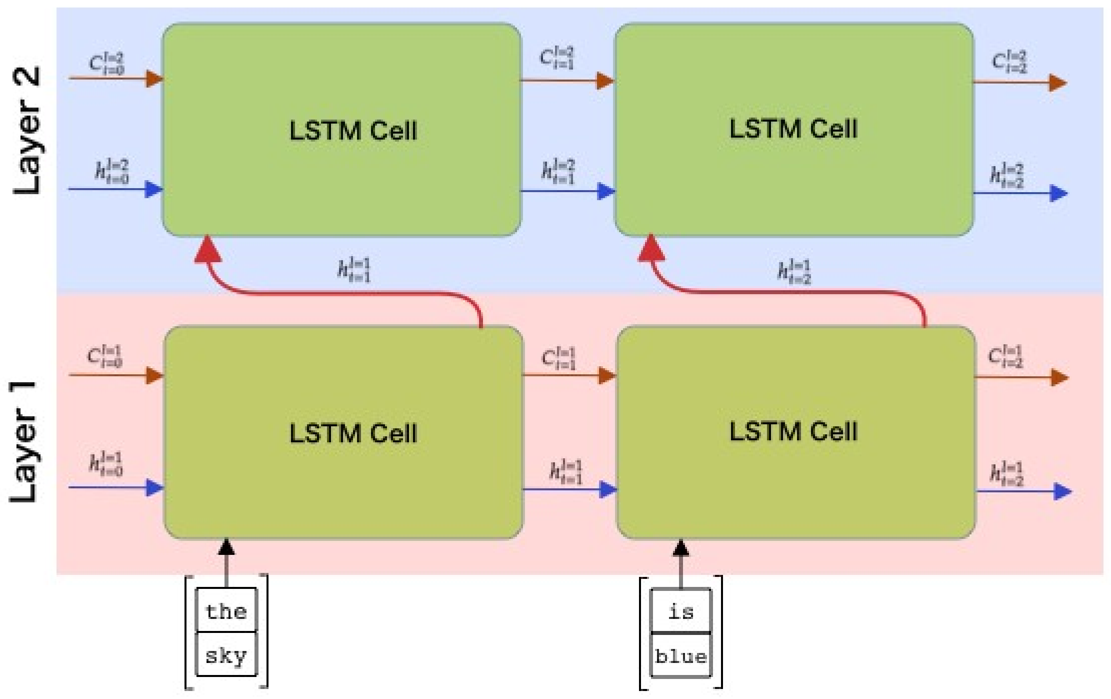
Components of the state C can be thought of as some flags that can be switched on and off. For example, when we encounter a name *Alice* in the sequence, we may want to assume that it refers to a female character, and raise the flag in the state that we have a female noun in the sentence. When we further encounter phrases *and Tom*, we will raise the flag that we have a plural noun. Thus by manipulating state we can supposedly keep track of the grammatical properties of sentence parts.

> ✅ An excellent resource for understanding the internals of LSTM is this great article Understanding LSTM Networks by Christopher Olah.

## Bidirectional and Multilayer RNNs

We have discussed recurrent networks that operate in one direction, from beginning of a sequence to the end. It looks natural, because it resembles the way we read and listen to speech. However, since in many practical cases we have random access to the input sequence, it might make sense to run recurrent computation in both directions. Such networks are call **bidirectional** RNNs. When dealing with bidirectional network, we would need two hidden state vectors, one for each direction.

A Recurrent network, either one-directional or bidirectional, captures certain patterns within a sequence, and can store them into a state vector or pass into output. As with convolutional networks, we can build another recurrent layer on top of the first one to capture higher level patterns and build from low-level patterns extracted by the first layer. This leads us to the notion of a **multi-layer RNN** which consists of two or more recurrent networks, where the output of the previous layer is passed to the next layer as input.



*Picture from this wonderful post by Fernando López*

## ✍️ Exercises: Embeddings

Continue your learning in the following notebooks:

- RNNs with PyTorch
- RNNs with TensorFlow

## Conclusion

In this unit, we have seen that RNNs can be used for sequence classification, but in fact, they can handle many more tasks, such as text generation, machine translation, and more. We will consider those tasks in the next unit.

## 🚀 Challenge

Read through some literature about LSTMs and consider their applications:

- Grid Long Short-Term Memory
- Show, Attend and Tell: Neural Image Caption Generation with Visual Attention

## Post-lecture quiz

## Review & Self Study

- Understanding LSTM Networks by Christopher Olah.

## Assignment: Notebooks

# Generative networks

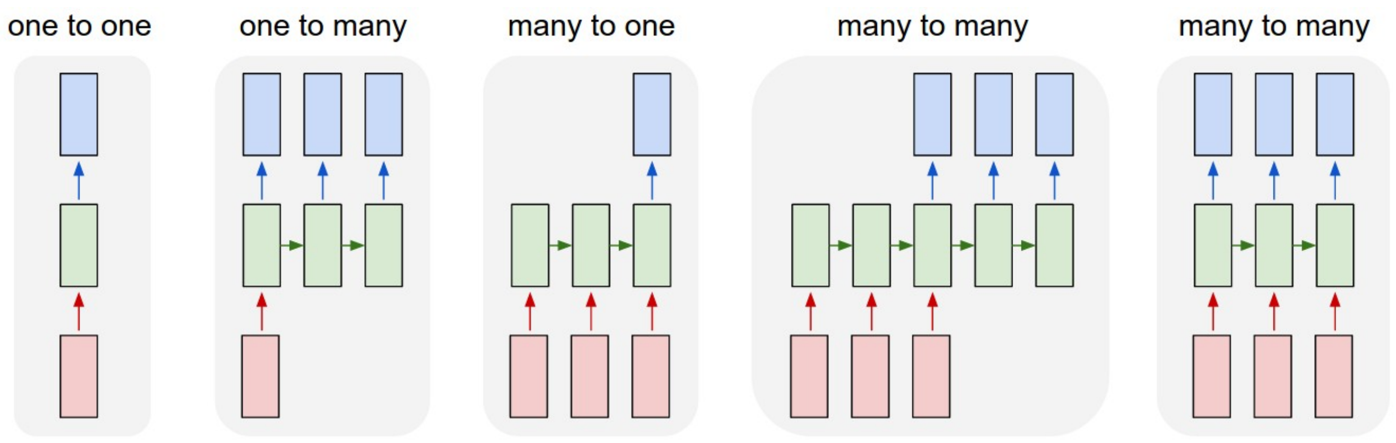
## Pre-lecture quiz

Recurrent Neural Networks (RNNs) and their gated cell variants such as Long Short Term Memory Cells (LSTMs) and Gated Recurrent Units (GRUs) provided a mechanism for language modeling in that they can learn word ordering and provide predictions for the next word in a sequence. This allows us to use RNNs for **generative tasks**, such as ordinary text generation, machine translation, and even image captioning.

> ✅ Think about all the times you've benefited from generative tasks such as text completion as you type. Do some research into your favorite applications to see if they leveraged RNNs.

In RNN architecture we discussed in the previous unit, each RNN unit produced the next hidden state as an output. However, we can also add another output to each recurrent unit, which would allow us to output a **sequence** (which is equal in length to the original sequence). Moreover, we can use RNN units that do not accept an input at each step, and just take some initial state vector, and then produce a sequence of outputs.

This allows for different neural architectures that are shown in the picture below:

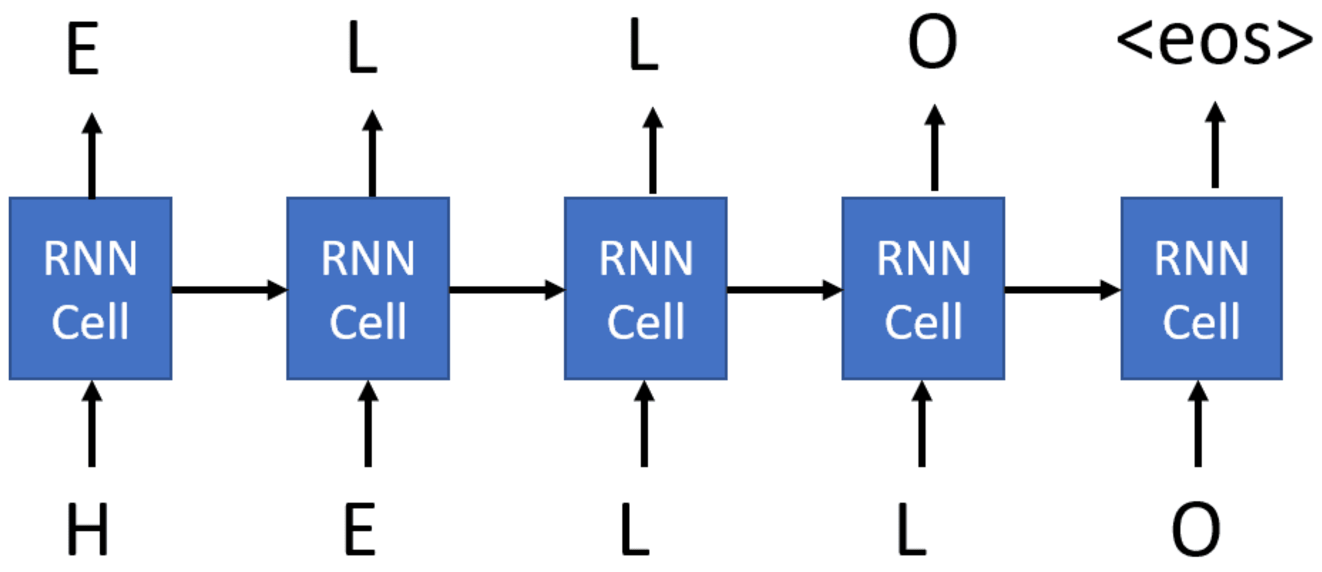


> Image from blog post Unreasonable Effectiveness of Recurrent Neural Networks by Andrej Karpaty

- **One-to-one** is a traditional neural network with one input and one output
- **One-to-many** is a generative architecture that accepts one input value, and generates a sequence of output values. For example, if we want to train an **image captioning** network that would produce a textual description of a picture, we can a picture as input, pass it through a CNN to obtain its hidden state, and then have a recurrent chain generate caption word-by-word
- **Many-to-one** corresponds to the RNN architectures we described in the previous unit, such as text classification
- **Many-to-many**, or **sequence-to-sequence** corresponds to tasks such as **machine translation**, where we have first RNN collect all information from the input sequence into the hidden state, and another RNN chain unrolls this state into the output sequence.

In this unit, we will focus on simple generative models that help us generate text. For simplicity, we will use character-level tokenization.

We will train this RNN to generate text step by step. On each step, we will take a sequence of characters of length `nchars` , and ask the network to generate the next output character for each input character:



When generating text (during inference), we start with some **prompt**, which is passed through RNN cells to generate its intermediate state, and then from this state the generation starts. We generate one character at a time, and pass the state and the generated character to another RNN cell to generate the next one, until we generate enough characters.

> Image by the author

## ✍️ Exercises: Generative Networks

Continue your learning in the following notebooks:

- Generative Networks with PyTorch
- Generative Networks with TensorFlow

## Soft text generation and temperature

The output of each RNN cell is a probability distribution of characters. If we always take the character with the highest probability as the next character in generated text, the text often can become "cycled" between the same character sequences again and again, like in this example:

```
today of the second the company and a second the company ...
```

However, if we look at the probability distribution for the next character, it could be that the difference between a few highest probabilities is not huge, e.g. one character can have probability 0.2, another - 0.19, etc. For example, when looking for the next character in the sequence '*play*', next character can equally well be either space, or **e** (as in the word *player*).

This leads us to the conclusion that it is not always "fair" to select the character with a higher probability, because choosing the second highest might still lead us to meaningful text. It is more wise to **sample** characters from the probability distribution given by the network output. We can also use a parameter, **temperature**, that will flatten out the probability distribution, in case we want to add more randomness, or make it more steep, if we want to stick more to the highest-probability characters.

Explore how this soft text generation is implemented in the notebooks linked above.

## Conclusion

While text generation may be useful in its own right, the major benefits come from the ability to generate text using RNNs from some initial feature vector. For example, text generation is used as part of machine translation (sequence-to-sequence, in this case state vector from *encoder* is used to generate or *decode* translated message), or generating textual description of an image (in which case the feature vector would come from CNN extractor).

## 🚀 Challenge

Take some lessons on Microsoft Learn on this topic

- Text Generation with PyTorch/TensorFlow

## Post-lecture quiz

## Review & Self Study

Here are some articles to expand your knowledge

- Different approaches to text generation with Markov Chain, LSTM and GPT-2: blog post
- Text generation sample in Keras documentation

## Assignment

We have seen how to generate text character-by-character. In the lab, you will explore word-level text generation.

# Attention Mechanisms and Transformers

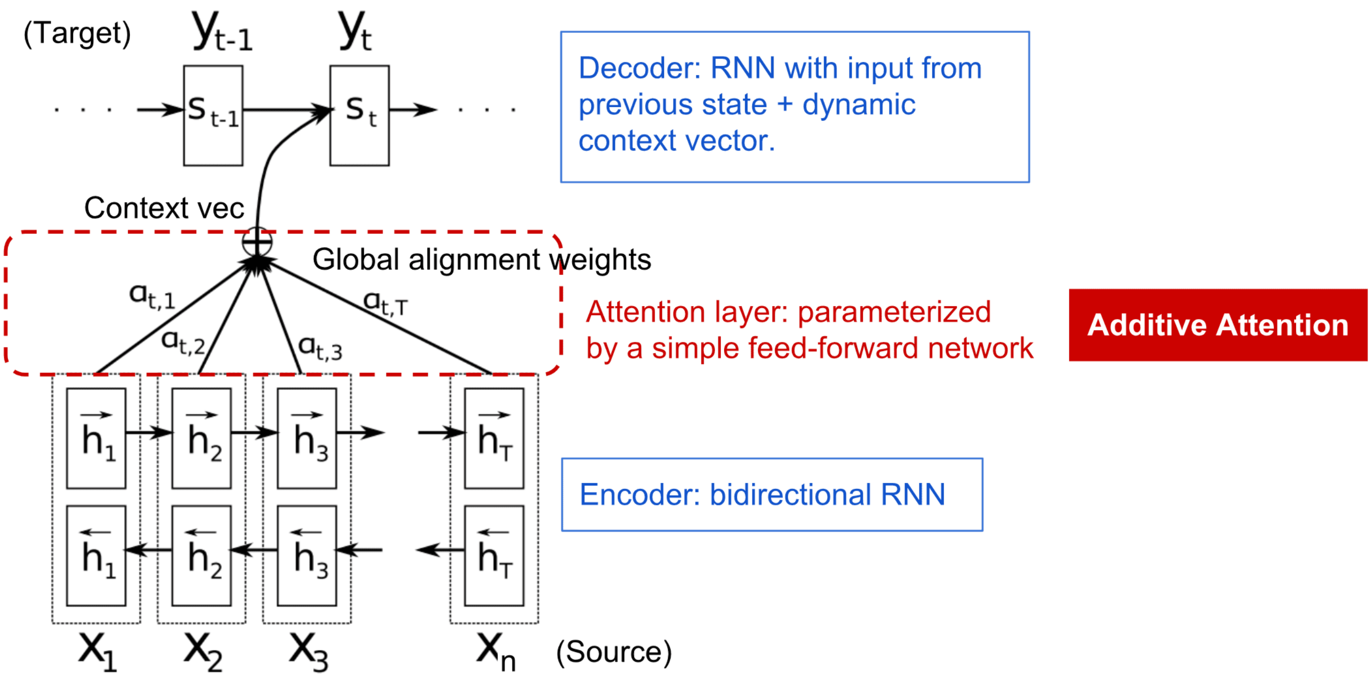
## Pre-lecture quiz

One of the most important problems in the NLP domain is **machine translation**, an essential task that underlies tools such as Google Translate. In this section, we will focus on machine translation, or, more generally, on any *sequence-to-sequence* task (which is also called **sentence transduction**).

With RNNs, sequence-to-sequence is implemented by two recurrent networks, where one network, the **encoder**, collapses an input sequence into a hidden state, while another network, the **decoder**, unrolls this hidden state into a translated result. There are a couple of problems with this approach:

- The final state of the encoder network has a hard time remembering the beginning of a sentence, thus causing poor quality of the model for long sentences
- All words in a sequence have the same impact on the result. In reality, however, specific words in the input sequence often have more impact on sequential outputs than others.

**Attention Mechanisms** provide a means of weighting the contextual impact of each input vector on each output prediction of the RNN. The way it is implemented is by creating shortcuts between intermediate states of the input RNN and the output RNN. In this manner, when generating output symbol $y_t$, we will take into account all input hidden states $h_i$, with different weight coefficients $\alpha_{t,i}$.


(Target)
$y_{t-1}$
$y_t$
$s_{t-1}$
$s_t$
Decoder: RNN with input from previous state + dynamic context vector.
Context vec
Global alignment weights
$a_{t,1}$
$a_{t,2}$
$a_{t,3}$
$a_{t,T}$
Attention layer: parameterized by a simple feed-forward network
Additive Attention
$\overrightarrow{h}_1$ $\overrightarrow{h}_2$ $\overrightarrow{h}_3$ $\overrightarrow{h}_T$
$\overleftarrow{h}_1$ $\overleftarrow{h}_2$ $\overleftarrow{h}_3$ $\overleftarrow{h}_T$
Encoder: bidirectional RNN
$X_1$ $X_2$ $X_3$ $X_n$
(Source)

> The encoder-decoder model with additive attention mechanism in Bahdanau et al., 2015, cited from this blog post

The attention matrix $\{\alpha_{i,j}\}$ would represent the degree that certain input words play in the generation of a given word in the output sequence. Below is an example of such a matrix:

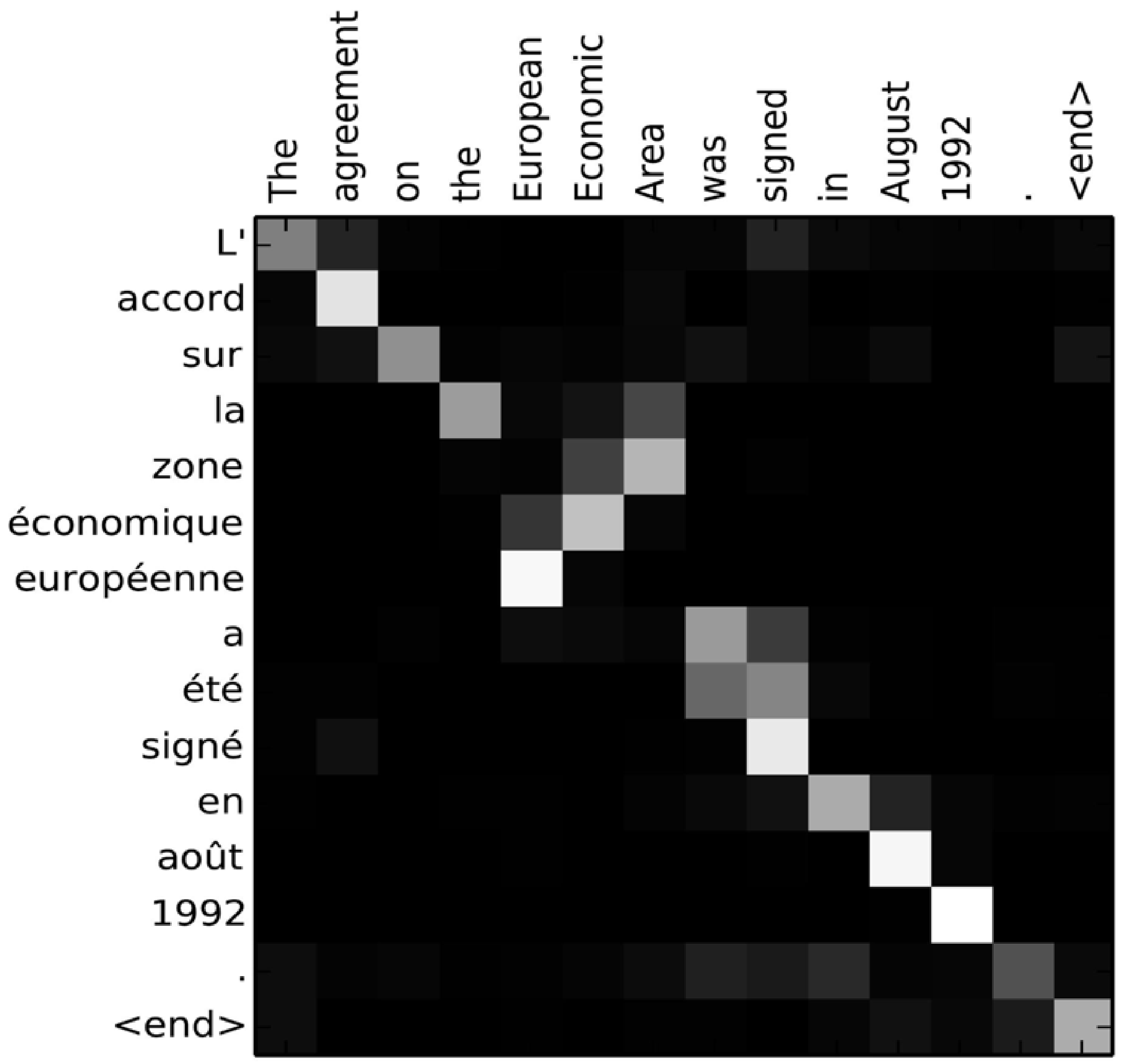
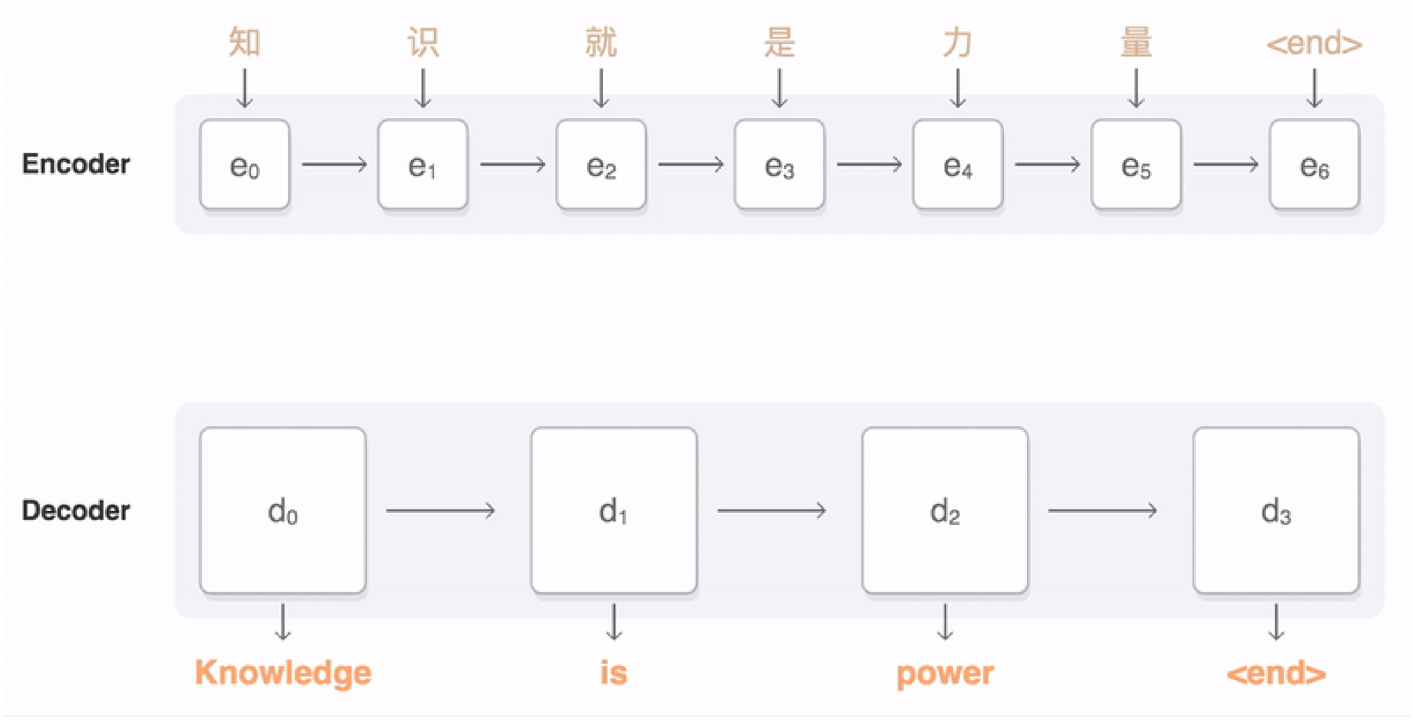


Figure from Bahdanau et al., 2015 (Fig.3)

Attention mechanisms are responsible for much of the current or near current state of the art in NLP. Adding attention however greatly increases the number of model parameters which led to scaling issues with RNNs. A key constraint of scaling RNNs is that the recurrent nature of the models makes it challenging to batch and parallelize training. In an RNN each element of a sequence needs to be processed in sequential order which means it cannot be easily parallelized.



> Figure from Google's Blog

The adoption of attention mechanisms combined with this constraint led to the creation of the now State of the Art Transformer Models that we know and use today such as BERT to Open-GPT3.

## Transformer models

One of the main ideas behind transformers is to avoid sequential nature of RNNs and to create a model that is parallelizable during training. This is achieved by implementing two ideas:

- positional encoding
- using self-attention mechanism to capture patterns instead of RNNs (or CNNs) (that is why the paper that introduces transformers is called *Attention is all you need*

### Positional Encoding/Embedding

The idea of positional encoding is the following.

1. When using RNNs, the relative position of the tokens is represented by the number of steps, and thus does not need to be explicitly represented.
2. However, once we switch to attention, we need to know the relative positions of tokens within a sequence.

3. To get positional encoding, we augment our sequence of tokens with a sequence of token positions in the sequence (i.e., a sequence of numbers 0,1, ...).
4. We then mix the token position with a token embedding vector. To transform the position (integer) into a vector, we can use different approaches:

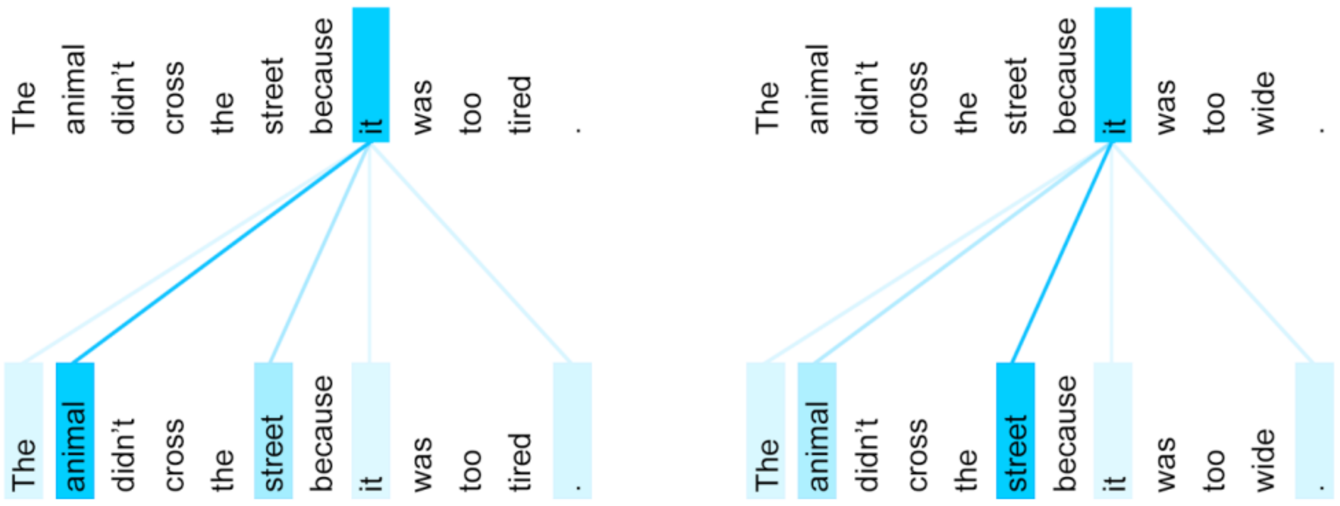
- Trainable embedding, similar to token embedding. This is the approach we consider here. We apply embedding layers on top of both tokens and their positions, resulting in embedding vectors of the same dimensions, which we then add together.
- Fixed position encoding function, as proposed in the original paper.

> Image by the author

The result that we get with positional embedding embeds both the original token and its position within a sequence.

## Multi-Head Self-Attention

Next, we need to capture some patterns within our sequence. To do this, transformers use a **self-attention** mechanism, which is essentially attention applied to the same sequence as the input and output. Applying self-attention allows us to take into account **context** within the sentence, and see which words are inter-related. For example, it allows us to see which words are referred to by coreferences, such as *it*, and also take the context into account:


The animal didn't cross the street because it was too tired .
The animal didn't cross the street because it was too tired .
The animal didn't cross the street because it was too wide .
The animal didn't cross the street because it was too wide .

> Image from the Google Blog

In transformers, we use **Multi-Head Attention** in order to give the network the power to capture several different types of dependencies, eg. long-term vs. short-term word relations, co-reference vs. something else, etc.

TensorFlow Notebook contains more detains on the implementation of transformer layers.

## Encoder-Decoder Attention

In transformers, attention is used in two places:

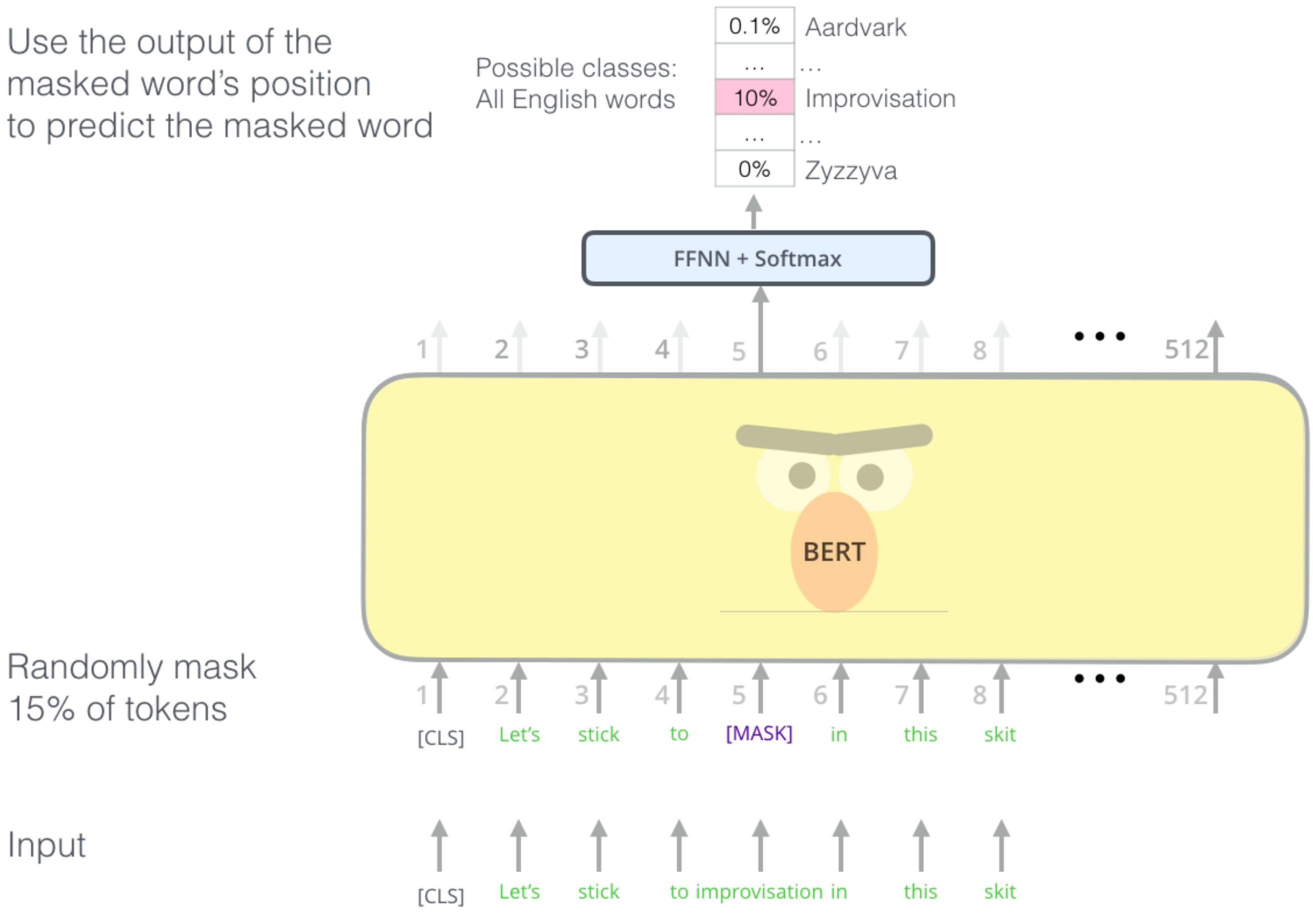
- To capture patterns within the input text using self-attention
- To perform sequence translation - it is the attention layer between encoder and decoder.

Encoder-decoder attention is very similar to the attention mechanism used in RNNs, as described in the beginning of this section. This animated diagram explains the role of encoder-decoder attention.

Since each input position is mapped independently to each output position, transformers can parallelize better than RNNs, which enables much larger and more expressive language models. Each attention head can be used to learn different relationships between words that improves downstream Natural Language Processing tasks.

# BERT

**BERT** (Bidirectional Encoder Representations from Transformers) is a very large multi layer transformer network with 12 layers for *BERT-base*, and 24 for *BERT-large*. The model is first pre-trained on a large corpus of text data (WikiPedia + books) using unsupervised training (predicting masked words in a sentence). During pre-training the model absorbs significant levels of language understanding which can then be leveraged with other datasets using fine tuning. This process is called **transfer learning**.



Use the output of the masked word's position to predict the masked word
Possible classes: All English words
0.1% Aardvark
...
10% Improvisation
...
0% Zyzzyva
FFNN + Softmax
1 2 3 4 5 6 7 8 ... 512
BERT
Randomly mask 15% of tokens
[CLS] Let's stick to [MASK] in this skit
Input
[CLS] Let's stick to improvisation in this skit

> Image source

## ✍️ Exercises: Transformers

Continue your learning in the following notebooks:

- Transformers in PyTorch
- Transformers in TensorFlow

## Conclusion

In this lesson you learned about Transformers and Attention Mechanisms, all essential tools in the NLP toolbox. There are many variations of Transformer architectures including BERT, DistilBERT.

BigBird, OpenGPT3 and more that can be fine tuned. The HuggingFace package provides repository for training many of these architectures with both PyTorch and TensorFlow.

## 🚀 Challenge

## Post-lecture quiz

## Review & Self Study

- Blog post, explaining the classical Attention is all you need paper on transformers.
- A series of blog posts on transformers, explaining the architecture in detail.

## Assignment

# Named Entity Recognition

Up to now, we have mostly been concentrating on one NLP task - classification. However, there are also other NLP tasks that can be accomplished with neural networks. One of those tasks is **Named Entity Recognition** (NER), which deals with recognizing specific entities within text, such as places, person names, date-time intervals, chemical formulae and so on.

## Pre-lecture quiz

## Example of Using NER

Suppose you want to develop a natural language chat bot, similar to Amazon Alexa or Google Assistant. The way intelligent chat bots work is to *understand* what the user wants by doing text classification on the input sentence. The result of this classification is so-called **intent**, which determines what a chat bot should do.

Bot NER

> Image by the author

However, a user may provide some parameters as part of the phrase. For example, when asking for the weather, she may specify a location or date. A bot should be able to understand those entities, and fill in the parameter slots accordingly before performing the action. This is exactly where NER comes in.

> ✅ Another example would be analyzing scientific medical papers. One of the main things we need to look for are specific medical terms, such as diseases and medical substances. While a small number of diseases can probably be extracted using substring search, more complex entities, such as chemical compounds and medication names, need a more complex approach.

## NER as Token Classification

NER models are essentially **token classification models**, because for each of the input tokens we need to decide whether it belongs to an entity or not, and if it does - to which entity class.

Consider the following paper title:

**Tricuspid valve regurgitation** and **lithium carbonate toxicity** in a newborn infant.

Entities here are:

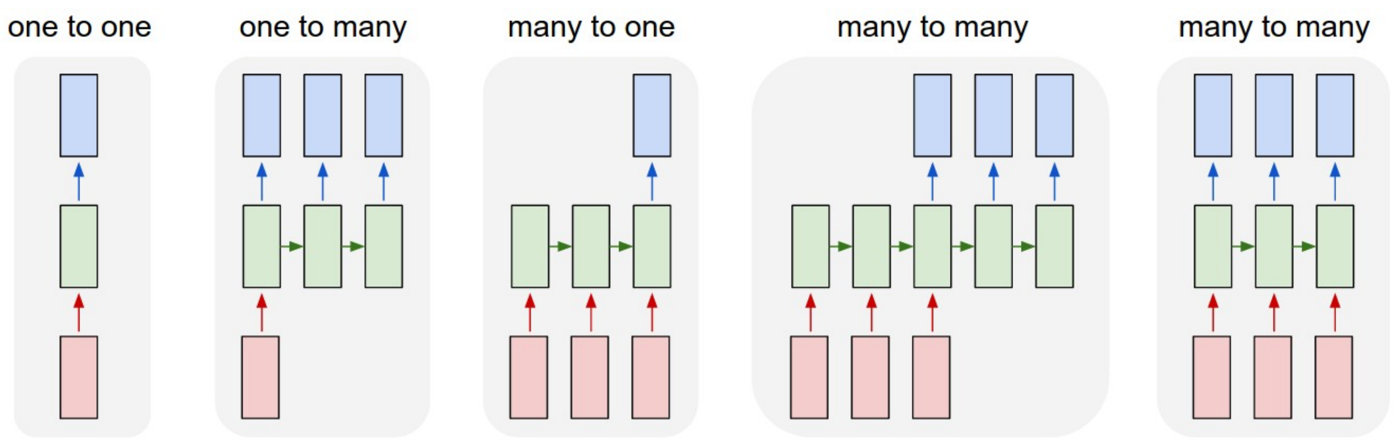
- Tricuspid valve regurgitation is a disease ( `DIS` )
- Lithium carbonate is a chemical substance ( `CHEM` )
- Toxicity is also a disease ( `DIS` )

Notice that one entity can span several tokens. And, as in this case, we need to distinguish between two consecutive entities. Thus it is common to use two classes for each entity - one specifying the first token of the entity (often the `B-` prefix is used, for **b**eginning), and another - the continuation of an entity ( `I-` , for **i**nner token). We also use `O` as a class to represent all **o**ther tokens. Such token tagging is called BIO tagging (or IOB). When tagged, our title will look like this:

| Token | Tag |
|---|---|

| Token | Tag |
|---|---|
| Tricuspid | B-DIS |
| valve | I-DIS |
| regurgitation | I-DIS |
| and | O |
| lithium | B-CHEM |
| carbonate | I-CHEM |
| toxicity | B-DIS |
| in | O |
| a | O |
| newborn | O |
| infant | O |
| . | O |

Since we need to build a one-to-one correspondence between tokens and classes, we can train a rightmost **many-to-many** neural network model from this picture:



> Image from this blog post by Andrej Karpathy. NER token classification models correspond to the right-most network architecture on this picture.

## Training NER models

Since a NER model is essentially a token classification model, we can use RNNs that we are already familiar with for this task. In this case, each block of recurrent network will return the token ID. The following example notebook shows how to train LSTM for token classification.

## ✍️ Example Notebooks: NER

Continue your learning in the following notebook:

- NER with TensorFlow

## Conclusion

A NER model is a **token classification model**, which means that it can be used to perform token classification. This is a very common task in NLP, helping to recognize specific entities within text including places, names, dates, and more.

## 🚀 Challenge

Complete the assignment linked below to train a named entity recognition model for medical terms, then try it on a different dataset.

## Post-lecture quiz

## Review & Self Study

Read through the blog The Unreasonable Effectiveness of Recurrent Neural Networks and follow along with the Further Reading section in that article to deepen your knowledge.

## Assignment

In the assignment for this lesson, you will have to train a medical entity recognition model. You can start with training an LSTM model as described in this lesson, and proceed with using the BERT transformer model. Read the instructions to get all the details.

# Pre-Trained Large Language Models

In all of our previous tasks, we were training a neural network to perform a certain task using labeled dataset. With large transformer models, such as BERT, we use language modelling in self-supervised fashion to build a language model, which is then specialized for specific downstream task with further domain-specific training. However, it has been demonstrated that large language models can also solve many tasks without ANY domain-specific training. A family of models capable of doing that is called **GPT**: Generative Pre-Trained Transformer.

## Pre-lecture quiz

## Text Generation and Perplexity

The idea of a neural network being able to do general tasks without downstream training is presented in Language Models are Unsupervised Multitask Learners paper. The main idea is the many other tasks can be modeled using **text generation**, because understanding text essentially means being able to produce it. Because the model is trained on a huge amount of text that encompasses human knowledge, it also becomes knowledgeable about wide variety of subjects.

> Understanding and being able to produce text also entails knowing something about the world around us. People also learn by reading to the large extent, and GPT network is similar in this respect.

Text generation networks work by predicting probability of the next word $P(w_N)$. However, unconditional probability of the next word equals to the frequency of the this word in the text corpus. GPT is able to give us **conditional probability** of the next word, given the previous ones $P(w_N | w_{n-1}, ..., w_0)$.

> You can read more about probabilities in our Data Science for Beginers Curriculum

Quality of language generating model can be defined using **perplexity**. It is intrinsic metric that allows us to measure the model quality without any task-specific dataset. It is based on the notion of *probability of a sentence* - the model assigns high probability to a sentence that is likely to be real (i.e. the model is not **perplexed** by it), and low probability to sentences that make less sense (eg. *Can it does what?*). When we give our model sentences from real text corpus, we would expect them to have high probability, and low **perplexity**. Mathematically, it is defined as normalized inverse probability of the test set: $$ \mathrm{Perplexity}(W) = \sqrt[N]{1\over P(W_1,...,W_N)} $$

**You can experiment with text generation using GPT-powered text editor from Hugging Face**. In this editor, you start writing your text, and pressing **[TAB]** will offer you several completion options. If they are too short, or you are not satisfied with them - press [TAB] again, and you will have more options, including longer pieces of text.

## GPT is a Family

GPT is not a single model, but rather a collection of models developed and trained by OpenAI. The latest model openly available is GPT-2, which has up to 1.5 billion parameters (there are several variations of the model, so you can select one for your tasks that is a good compromise between size/performance). Latest GPT-3 model has up to 175 billion parameters, and is available as a cognitive service from Microsoft Azure, and as OpenAI API.

## Prompt-based Inference

Because GPT has been trained on a vast volumes of data, it has some commonsense knowledge embedded directly inside the model. This allows us to force GPT to solve certain typical problems by just providing the right prompt. This presents a whole new approach for using pre-trained models, called Prompt Engineering. It is particularly useful with GPT-3, which has significantly more parameters, and consequently more embedded knowledge.

Here are a few example of using Prompt Engineering (answers from the model are *in italics*):

**Recommendation Systems**:
People, who liked the movie "The Matrix" also liked *Star Wars, Jupyter Ascending, Ex Machina*

**Translation**:
Translate from English to French:
cat => chat, dog => chien, student => *étudiant*

**Looking for words:**
Synonyms of a word cat: *feline, feline form, feline spirit*

This article talks more about prompt engineering.

## ✍️ Example Notebook:Playing with GPT-2

Continue your learning in the following notebooks:

- Generating text with GPT-2 and Hugging Face Transformers

## Conclusion

New general pre-trained language models do not only model language structure, but also contain vast amount of commonsense knowledge. Thus, they can be effectively used to solve some NLP tasks in zero-shop or few-shot settings.

## Post-lecture quiz

# Genetic Algorithms

## Pre-lecture quiz

**Genetic Algorithms** (GA) are based on an **evolutionary approach** to AI, in which methods of the evolution of a population is used to obtain an optimal solution for a given problem. They were proposed in 1975 by John Henry Holland.

Genetic Algorithms are based on the following ideas:

- Valid solutions to the problem can be represented as **genes**
- **Crossover** allows us to combine two solutions together to obtain a new valid solution

- **Selection** is used to select more optimal solutions using some **fitness function**
- **Mutations** are introduced to destabilize optimization and get us out of the local minimum

If you want to implement a Genetic Algorithm, you need the following:

- To find a method of coding our problem solutions using **genes** $g \in \Gamma$
- On the set of genes $\Gamma$ we need to define **fitness function** fit: $\Gamma \to \mathbf{R}$. Smaller function values correspond to better solutions.
- To define **crossover** mechanism to combine two genes together to get a new valid solution crossover: $\Gamma^{2 \to \Gamma.}$
- To define **mutation** mechanism mutate: $\Gamma \to \Gamma$.

In many cases, crossover and mutation are quite simple algorithms to manipulate genes as numeric sequences or bit vectors.

The specific implementation of a genetic algorithm can vary from case to case, but the overall structure is the following:

1. Select an initial population $G \subset \Gamma$
2. Randomly select one of the operations that will be performed at this step: crossover or mutation
3. **Crossover**:

- Randomly select two genes $g_1, g_2 \in G$
- Compute crossover $g = \text{crossover}(g_1, g_2)$
- If $\text{fit}(g) < \text{fit}(g_1)$ or $\text{fit}(g) < \text{fit}(g_2)$ - replace corresponding gene in the population by g.

4. **Mutation** - select random gene $g \in G$ and replace it by mutate(g)
5. Repeat from step 2, until we get a sufficiently small value of fit, or until the limit on the number of steps is reached.

## Typical Tasks

Tasks typically solved by Genetic Algorithms include:

1. Schedule optimization
2. Optimal packing
3. Optimal cutting
4. Speeding up exhaustive search

## ✍️ Exercises: Genetic Algorithms

Continue your learning in the following notebooks:

Go to this notebook to see two examples of using Genetic Algorithms:

1. Fair division of treasure
2. 8 Queens Problem

## Conclusion

Genetic Algorithms are used to solve many problems, including logistics and search problems. The field is Inspired by research that merged topics in Psychology and Computer Science.

## 🚀 Challenge

"Genetic algorithms are simple to implement, but their behavior is difficult to understand." source Do some research to find an implementation of a genetic algorithm such as solving a Sudoku puzzle, and explain how it works as a sketch or flowchart.

## Post-lecture quiz

## Review & Self Study

Watch this great video talking about how computer can learn to play Super Mario using neural networks trained by genetic algorithms. We will learn more about computer learning to play games like that in the next section.

## Assignment: Diophantine Equation

Your goal is to solve so-called **Diophantine equation** - an equation with integer roots. For example, consider the equation a+2b+3c+4d=30. You need to find the integer roots that satisfy this equation.

*This assignment is inspired by this post.*

Hints:

1. You can consider roots to be in the interval [0;30]
2. As a gene, consider using the list of root values

Use Diophantine.ipynb as a starting point.

# Deep Reinforcement Learning

Reinforcement learning (RL) is seen as one of the basic machine learning paradigms, next to supervised learning and unsupervised learning. While in supervised learning we rely on the dataset with known outcomes, RL is based on **learning by doing**. For example, when we first see a computer game, we start playing, even without knowing the rules, and soon we are able to improve our skills just by the process of playing and adjusting our behavior.

## Pre-lecture quiz

To perform RL, we need:

- An **environment** or **simulator** that sets the rules of the game. We should be able to run the experiments in the simulator and observe the results.
- Some **Reward function**, which indicates how successful our experiment was. In case of learning to play a computer game, the reward would be our final score.

Based on the reward function, we should be able to adjust our behavior and improve our skills, so that the next time we play better. The main difference between other types of machine learning and RL is that in RL we typically do not know whether we win or lose until we finish the game. Thus, we cannot say whether a certain move alone is good or not - we only receive a reward at the end of the game.

During RL, we typically perform many experiments. During each experiment, we need to balance between following the optimal strategy that we have learned so far (**exploitation**) and exploring new possible states (**exploration**).

## OpenAI Gym

A great tool for RL is the OpenAI Gym - a **simulation environment**, which can simulate many different environments starting from Atari games, to the physics behind pole balancing. It is one of the most popular simulation environments for training reinforcement learning algorithms, and is maintained by OpenAI.

> **Note**: You can see all the environments available from OpenAI Gym here.

## CartPole Balancing

You have probably all seen modern balancing devices such as the *Segway* or *Gyroscooters*. They are able to automatically balance by adjusting their wheels in response to a signal from accelerometer or gyroscope. In this section, we will learn how to solve a similar problem - balancing a pole. It is similar to a situation when a circus performer needs to balance a pole on his hand - but this pole balancing only occurs in 1D.

A simplified version of balancing is known as a **CartPole** problem. In the cartpole world, we have a horizontal slider that can move left or right, and the goal is to balance a vertical pole on top of the slider as it moves.

a cartpole

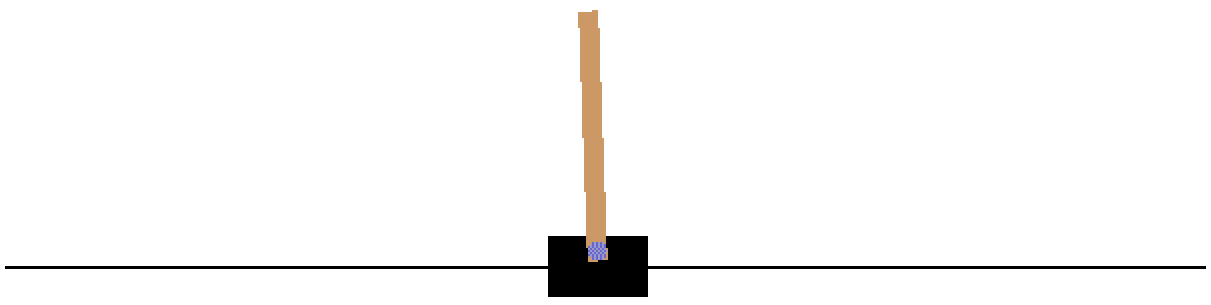
To create and use this environment, we need a couple of lines of Python code:

```python
import gym
env = gym.make("CartPole-v1")

env.reset()
done = False
total_reward = 0
while not done:
   env.render()
   action = env.action_space.sample()
   observaton, reward, done, info = env.step(action)
   total_reward += reward

print(f"Total reward: {total_reward}")
```

Each environment can be accessed exactly in the same way:

- `env.reset` starts a new experiment
- `env.step` performs a simulation step. It receives an **action** from the **action space**, and returns an **observation** (from the observation space), as well as a reward and a termination flag.

In the example above we perform a random action at each step, which is why the experiment life is very short:



The goal of a RL algorithm is to train a model - the so called **policy** π - which will return the action in response to a given state. We can also consider policy to be probabilistic, eg. for any state *s* and action *a* it will return the probability π(*a*|*s*) that we should take *a* in state *s*.

## Policy Gradients Algorithm

The most obvious way to model a policy is by creating a neural network that will take states as input, and return corresponding actions (or rather the probabilities of all actions). In a sense, it would be similar to a normal classification task, with a major difference - we do not know in advance which actions should we take at each of the steps.

The idea here is to estimate those probabilities. We build a vector of **cumulative rewards** which shows our total reward at each step of the experiment. We also apply **reward discounting** by multiplying earlier rewards by some coefficient γ=0.99, in order to diminish the role of earlier rewards. Then, we reinforce those steps along the experiment path that yield larger rewards.

> Learn more about the Policy Gradient algorithm and see it in action in the example notebook.

## Actor-Critic Algorithm

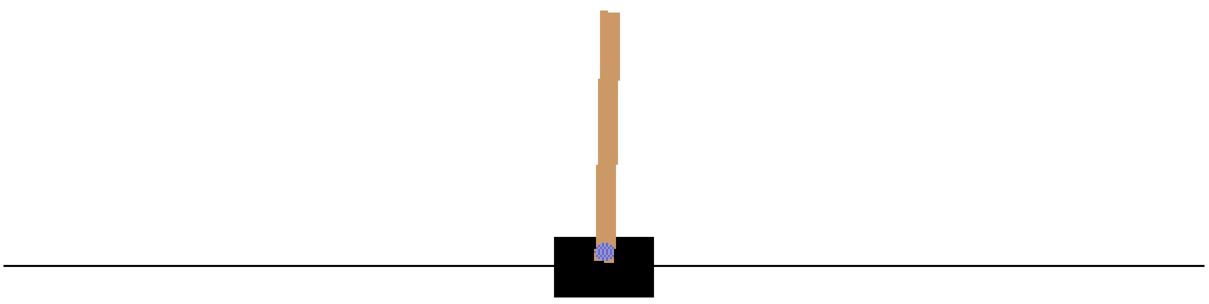
An improved version of the Policy Gradients approach is called **Actor-Critic**. The main idea behind it is that the neural network would be trained to return two things:

- The policy, which determines which action to take. This part is called **actor**
- The estimation of the total reward we can expect to get at this state - this part is called **critic**.

In a sense, this architecture resembles a GAN, where we have two networks that are trained against each other. In the actor-critic model, the actor proposes the action we need to take, and the critic tries to be critical and estimate the result. However, our goal is to train those networks in unison.

Because we know both the real cumulative rewards and the results returned by the critic during the experiment, it is relatively easy to build a loss function that will minimize the difference between them. That would give us **critic loss**. We can compute **actor loss** by using the same approach as in the policy gradient algorithm.

After running one of those algorithms, we can expect our CartPole to behave like this:



## ✍️ Exercises: Policy Gradients and Actor-Critic RL

Continue your learning in the following notebooks:

- RL in TensorFlow

## Other RL Tasks

Reinforcement Learning nowadays is a fast growing field of research. Some of the interesting examples of reinforcement learning are:

- Teaching a computer to play **Atari Games**. The challenging part in this problem is that we do not have simple state represented as a vector, but rather a screenshot - and we need to use the CNN to convert this screen image to a feature vector, or to extract reward information. Atari games are available in the Gym.
- Teaching a computer to play board games, such as Chess and Go. Recently state-of-the-art programs like **Alpha Zero** were trained from scratch by two agents playing against each other, and improving at each step.
- In industry, RL is used to create control systems from simulation. A service called Bonsai is specifically designed for that.

## Conclusion

We have now learned how to train agents to achieve good results just by providing them a reward function that defines the desired state of the game, and by giving them an opportunity to intelligently explore the search space. We have successfully tried two algorithms, and achieved a good result in a relatively short period of time. However, this is just the beginning of your journey into RL, and you should definitely consider taking a separate course is you want to dig deeper.

## 🚀 Challenge

Explore the applications listed in the 'Other RL Tasks' section and try to implement one!

## Post-lecture quiz

## Review & Self Study

Learn more about classical reinforcement learning in our Machine Learning for Beginners Curriculum.

Watch this great video talking about how a computer can learn to play Super Mario.

## Assignment: Train a Mountain Car

Your goal during this assignment would be to train a different Gym environment - Mountain Car.

# Multi-Agent Systems

One of the possible ways of achieving intelligence is so-called **emergent** (or **synergetic**) approach, which is based on the fact that the combined behavior of many relatively simple agents can result in the overall more complex (or intelligent) behavior of the system as a whole. Theoretically, this is based on the principles of Collective Intelligence, Emergentism and Evolutionary Cybernetics, which state that higher-level systems gain some sort of added value when being properly combined from lower-level systems (so-called *principle of metasystem transition*).

## Pre-lecture quiz

The direction of **Multi-Agent Systems** has emerged in AI in 1990s as a response to growth of the Internet and distributed systems. On of the classical AI textbooks, Artificial Intelligence: A Modern Approach, focuses on the view of classical AI from the point of view of Multi-agent systems.

Central to Multi-agent approach is the notion of **Agent** - an entity that lives in some **environment**, which it can perceive, and act upon. This is a very broad definition, and there could be many different types and classifications of agents:

- By their ability to reason:
  - **Reactive** agents usually have simple request-response type of behavior
  - **Deliberative** agents employ some sort of logical reasoning and/or planning capabilities
- By the place where agent execute its code:
  - **Static** agents work on a dedicated network node
  - **Mobile** agents can move their code between network nodes
- By their behavior:
  - **Passive agents** do not have specific goals. Such agents can react to external stimuli, but will not initiate any actions themselves.
  - **Active agents** have some goals which they pursue
  - **Cognitive agents** involve complex planning and reasoning

Multi-agent systems are nowadays used in a number of applications:

- In games, many non-player characters employ some sort of AI, and can be considered to be intelligent agents
- In video production, rendering complex 3D scenes that involve crowds is typically done using multi-agent simulation
- In systems modeling, multi-agent approach is used to simulate the behavior of a complex model. For example, multi-agent approach has been successfully used to predict the spread of COVID-19 disease worldwide. Similar approach can be used to model traffic in the city, and see how it reacts to changes in traffic rules.
- In complex automation systems, each device can act as an independent agent, which makes the whole system less monolith and more robust.

We will not spend a lot of time going deep into multi-agent systems, but consider one example of **Multi-Agent Modeling**.

## NetLogo

NetLogo is a multi-agent modeling environment based on a modified version of the Logo programming language. This language was developed for teaching programming concepts to kids, and it allows you to control an agent called **turtle**, which can move, leaving a trace behind. This allows creating complex geometric figures, which is a very visual way to understand the behavior of an agent.

In NetLogo, we can create many turtles by using the `create-turtles` command. We can then command all turtles to do some actions (in the example below - more 10 point forward):

```
create-turtles 10
ask turtles [
  forward 10
]
```

Of course, it is not interesting when all turtles do the same thing, so we can `ask` groups of turtles, eg. those who are in the vicinity of a certain point. We can also create turtles of different *breeds* using `breed [cats cat]` command. Here `cat` is the name of a breed, and we need to specify both singular and plural word, because different commands use different forms for clarity.

> ✅ We will not go into learning the NetLogo language itself - you can visit the brilliant Beginner's Interactive NetLogo Dictionary resource if you are interested in learning more.

You can download and install NetLogo to try it.

## Models Library

A great thing about NetLogo is that it contains a library of working models that you can try. Go to **File → Models Library**, and you have many categories of models to choose from.

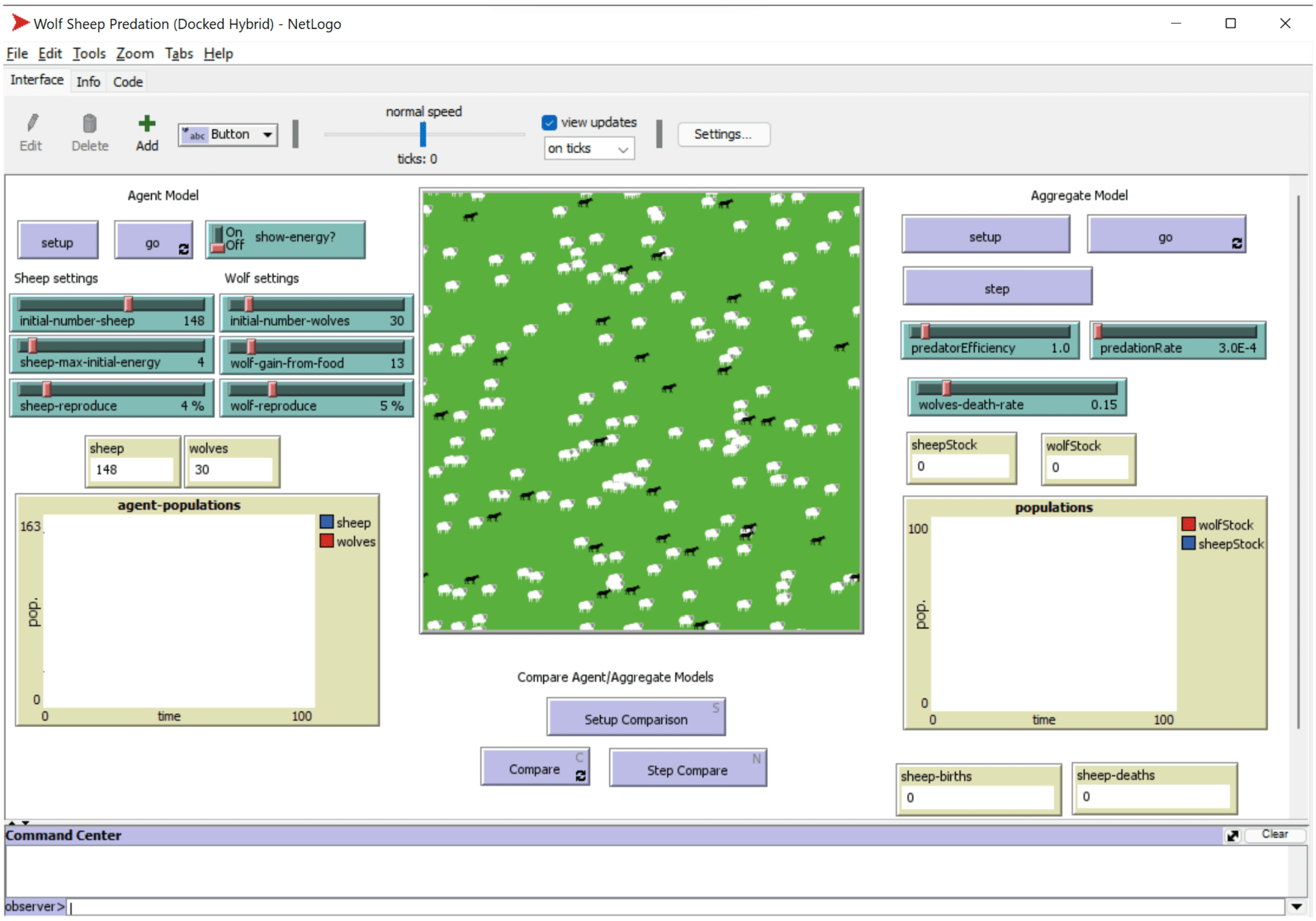
NetLogo Models Library

> A screenshot of the models library by Dmitry Soshnikov

You can open one of the models, for example **Biology → Flocking**.

## Main Principles

After opening the model, you are taken to the main NetLogo screen. Here is a sample model that describes the population of wolves and sheep, given finite resources (grass).



ticks: 0
on ticks
show-energy? Off
initial-number-sheep 148
sheep-max-initial-energy 4
sheep-reproduce 4 %
initial-number-wolves 30
wolf-gain-from-food 13
wolf-reproduce 5 %
sheep 148
wolves 30
predatorEfficiency 1.0
predationRate 3.0E-4
wolves-death-rate 0.15
sheepStock 0
wolfStock 0
sheep-births 0
sheep-deaths 0

> Screenshot by Dmitry Soshnikov

On this screen, you can see:

- The **Interface** section which contains:
  - The main field, where all agents live
  - Different controls: buttons, sliders, etc.
  - Graphs that you can use to display parameters of the simulation
- The **Code** tab which contains the editor, where you can type NetLogo program

In most cases, the interface would have a **Setup** button, which initializes the simulation state, and a **Go** button that starts the execution. Those are handled by corresponding handlers in the code that look like this:

```
to go [
...
]
```

NetLogo's world consists of the following objects:

- **Agents** (turtles) that can move across the field and do something. You command agents by using `ask turtles [...]` syntax, and the code in brackets is executed by all agents in *turtle mode*.
- **Patches** are square areas of the field, on which agents live. You can refer to all agents on the same patch, or you can change patch colors and some other properties. You can also `ask patches` to do something.
- **Observer** is a unique agent that controls the world. All button handlers are executed in *observer mode*.

> ✅ The beauty of a multi-agent environment is that the code that runs in turtle mode or in patch mode is executed at the same time by all agents in parallel. Thus, by writing a little code and programming the behavior of individual agent, you can create complex behavior of the simulation system as a whole.

## Flocking

As an example of multi-agent behavior, let's consider **Flocking**. Flocking is a complex pattern that is very similar to how flocks of birds fly. Watching them fly you can think that they follow some kind of collective algorithm, or that they possess some form of *collective intelligence*. However, this complex behavior arises when each individual agent (in this case, a *bird*) only observes some other agents in a short distance from it, and follows three simple rules:

- **Alignment** - it steers towards the average heading of neighboring agents
- **Cohesion** - it tries to steer towards the average position of neighbors (*long range attraction*)
- **Separation** - when getting too close to other birds, it tries to move away (*short range repulsion*)

You can run the flocking example and observe the behavior. You can also adjust parameters, such as *degree of separation*, or the *viewing range*, which defines how far each bird can see. Note that if you decrease the viewing range to 0, all birds become blind, and flocking stops. If you decrease separation to 0, all birds gather into a straight line.

> ✅ Switch to the **Code** tab and see where three rules of flocking (alignment, cohesion and separation) are implemented in code. Note how we refer only to those agents that are in sight.

## Other Models to see

There are a few more interesting models that you can experiment with:

- **Art → Fireworks** shows how a firework can be considered a collective behavior of individual fire streams
- **Social Science → Traffic Basic** and **Social Science → Traffic Grid** show the model of city traffic in 1D and 2D Grid with or without traffic lights. Each car in the simulation follows the following rules:
  - If the space in front of it is empty - accelerate (up to a certain max speed)
  - If it sees the obstacle in front - brake (and you can adjust how far a driver can see)
- **Social Science → Party** shows how people group together during a cocktail party. You can find the combination of parameters that lead to the fastest increase of happiness of the group.

As you can see from these examples, multi-agent simulations can be quite a useful way to understand the behavior of a complex system consisting of individuals that follow the same or similar logic. It can also be used to control virtual agents, such as NPCs in computer games, or agents in 3D animated worlds.

## Deliberative Agents

The agents described above are very simple, reacting to changes in environment using some kind of algorithm. As such they are **reactive agents**. However, sometimes agents can reason and plan their action, in which case they are called **deliberative**.

A typical example would be a personal agent that receives an instruction from a human to book a vacation tour. Suppose that there are many agents that live on the internet, who can help it. It should then contact other agents to see which flights are available, what are the hotel prices for different dates, and try to negotiate the best price. When the vacation plan is complete and confirmed by the owner, it can proceed with booking.

In order to do that, agents need to **communicate**. For successful communication they need:

- Some **standard languages to exchange knowledge**, such as Knowledge Interchange Format (KIF) and Knowledge Query and Manipulation Language (KQML). Those languages are designed based on Speech Act theory.
- Those languages should also include some **protocols for negotiations**, based on different **auction types**.
- A **common ontology** to use, so that they refer to the same concepts knowing their semantics
- A way to **discover** what different agents can do, also based on some sort of ontology

Deliberative agents are much more complex than reactive, because they do not only react to changes in environment, they should also be able to *intiate* actions. One of the proposed architectures for deliberative agents is the so-called Belief-Desire-Intention (BDI) agent:

- **Beliefs** form a set of knowledge about an agent's environment. It can be structured as a knowledge base or set of rules that an agent can apply to a specific situation in the environment.
- **Desires** define what an agent wants to do, i.e. its goals. For example, the goal of the personal assistant agent above is to book a tour, and the goal of a hotel agent is to maximize profit.
- **Intentions** are specific actions that an agent plans to achieve its goals. Actions typically change the environment and cause communication with other agents.

There are some platforms available for building multi-agent systems, such as JADE. This paper contains a review of multi-agent platforms, together with a brief history of multi-agent systems and their different usage scenarios.

## Conclusion

Multi-Agent systems can take very different forms and be used in many different applications. They all tend to focus on the simpler behavior of an individual agent, and achieve more complex behavior of the overall system due to **synergetic effect**.

## 🚀 Challenge

Take this lesson to the real world and try to conceptualize a multi-agent system that can solve a problem. What, for example, would a multi-agent system need to do to optimize a school bus route? How could it work in a bakery?

## Post-lecture quiz

## Review & Self Study

Review the use of this type of system in industry. Pick a domain such as manufacturing or the video game industry and discover how multi-agent systems can be used to solve unique problems.

## NetLogo Assignment

# Ethical and Responsible AI

You have almost finished this course, and I hope that by now you clearly see that AI is based on a number of formal mathematical methods that allow us to find relationships in data and train models to replicate some aspects of human behavior. At this point in history, we consider AI to be a very powerful tool to extract patterns from data, and to apply those patterns to solve new problems.

## Pre-lecture quiz

However, in science fiction we often see stories where AI presents a danger to humankind. Usually those stories are centered around some sort of AI rebellion, when AI decides to confront human beings. This implies that AI has some sort of emotion or can take decisions unforeseen by its developers.

The kind of AI that we have learned about in this course is nothing more than large matrix arithmetic. It is a very powerful tool to help us solve our problems, and as any other powerful tool - it can be used for good and for bad purposes. Importantly, it can be *misused*.

## Principles of Responsible AI

To avoid this accidental or purposeful misuse of AI, Microsoft states the important Principles of Responsible AI. The following concepts underpin these principles:

- **Fairness** is related to the important problem of *model biases*, which can be caused by using biased data for training. For example, when we try to predict the probability of getting a software developer job for a person, the model is likely to give higher preference to males - just because the training dataset was likely biased towards a male audience. We need to carefully balance training data and investigate the model to avoid biases, and make sure that the model takes into account more relevant features.
- **Reliability and Safety**. By their nature, AI models can make mistakes. A neural network returns probabilities, and we need to take it into account when making decisions. Every model has some precision and recall, and we need to understand that to prevent harm that wrong advice can cause.
- **Privacy and Security** have some AI-specific implications. For example, when we use some data for training a model, this data becomes somehow "integrated" into the model. On one hand, that increases security and privacy, on the other - we need to remember which data the model was trained on.
- **Inclusiveness** means that we are not building AI to replace people, but rather to augment people and make our work more creative. It is also related to fairness, because when dealing with underrepresented communities, most of the datasets we collect are likely to be biased, and we need to make sure that those communities are included and correctly handled by AI.
- **Transparency**. This includes making sure that we are always clear about AI being used. Also, wherever possible, we want to use AI systems that are *interpretable*.
- **Accountability**. When AI models come up with some decisions, it is not always clear who is responsible for those decisions. We need to make sure that we understand where responsibility of AI decisions lies. In most cases we would want to include human beings into the loop of making important decisions, so that actual people are made accountable.

## Tools for Responsible AI

Microsoft has developed the Responsible AI Toolbox which contains a set of tools:

- Interpretability Dashboard (InterpretML)

- Fairness Dashboard (FairLearn)

- Error Analysis Dashboard
- Responsible AI Dashboard that includes
    - EconML - tool for Causal Analysis, which focuses on what-if questions
    - DiCE - tool for Counterfactual Analysis allows you to see which features need to be changed to affect the decision of the model

For more information about AI Ethics, please visit this lesson on the Machine Learning Curriculum which includes assignments.

## Review & Self Study

Take this Learn Path to learn more about responsible AI.

## Post-lecture quiz