ML: A Framework for Understanding The AI Landscape & Terminology

David Yakobovitch, Galvanize

Enterprise Talent Transformation

Assessment

Identify skills gaps and weak spots to map learning pathways for growth.

Ideal For	Duration
Software Development Teams	*30 - 60 min Per Assessment*

Onboarding

Get new hires up-to-speed and confident on your technologies in your environment.

Ideal For	Duration
Computer Science Grads and Bootcamp Grads	*2 - 3 Weeks*

Reskilling

Train non-tech employees to become developers using our proven coding bootcamp approach.

Ideal For	Duration
Non-Technical Professionals	*12 - 24 Weeks*

Upskilling

Re-tool your senior developers on the newest technologies and practices to improve performance.

Ideal For	Duration
Experienced Engineers	*2 Days - 4 Weeks*

Abstract: Data Science & AI Survey

Learning Objectives:

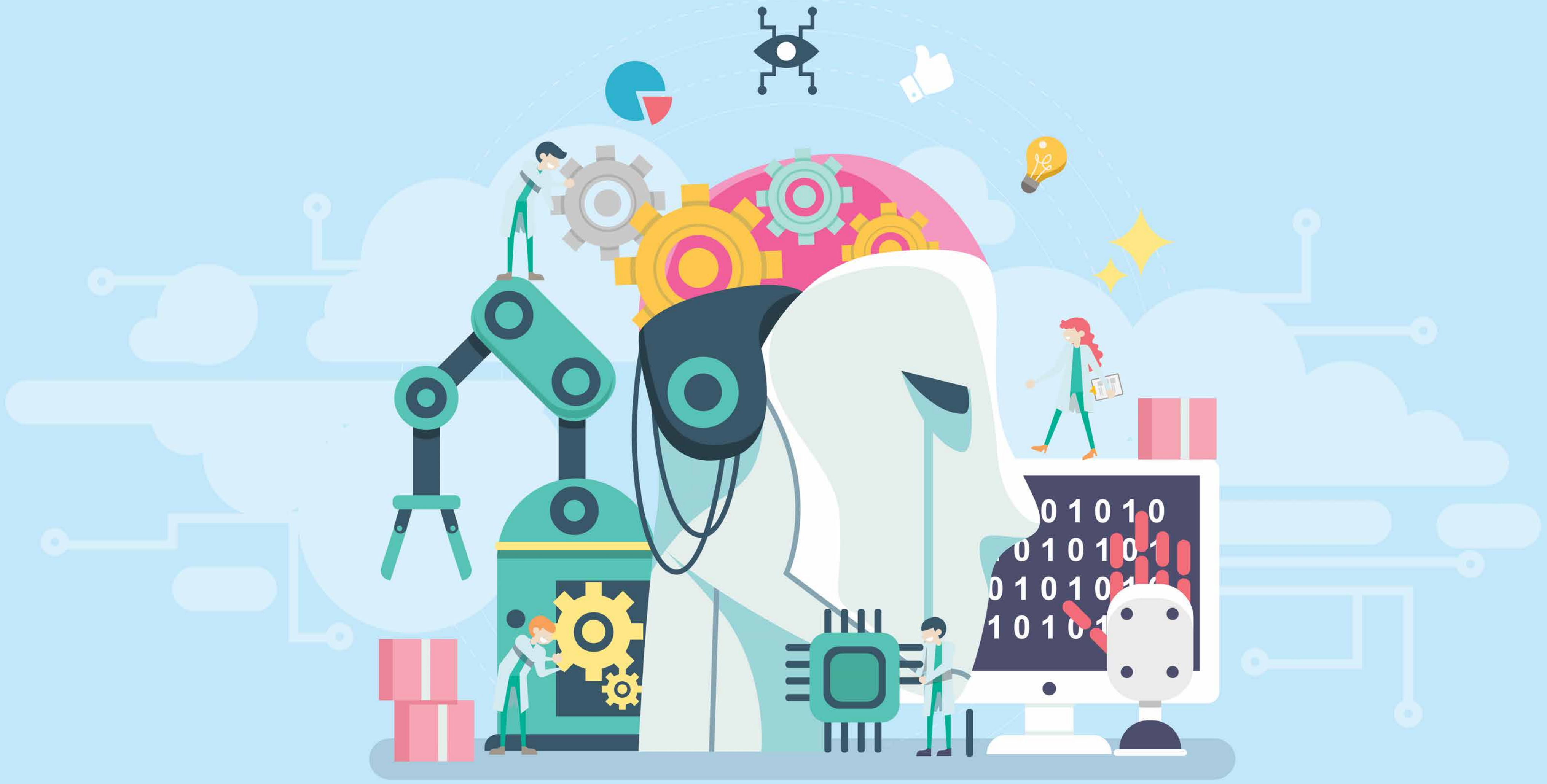
Part 1:

1. **AI Landscape I (4-17)**
2. **Common Language (18-29)**
3. **Data Science Workflow (30-38)**

Part 2:

1. **AI Landscape II (40-45)**
2. **Algorithms (46-70)**
3. **Common Challenges (71-75)**
4. **AI Demos (76-80)**
5. **AI Ethics (81-88)**

Is it AI or ML or DL?



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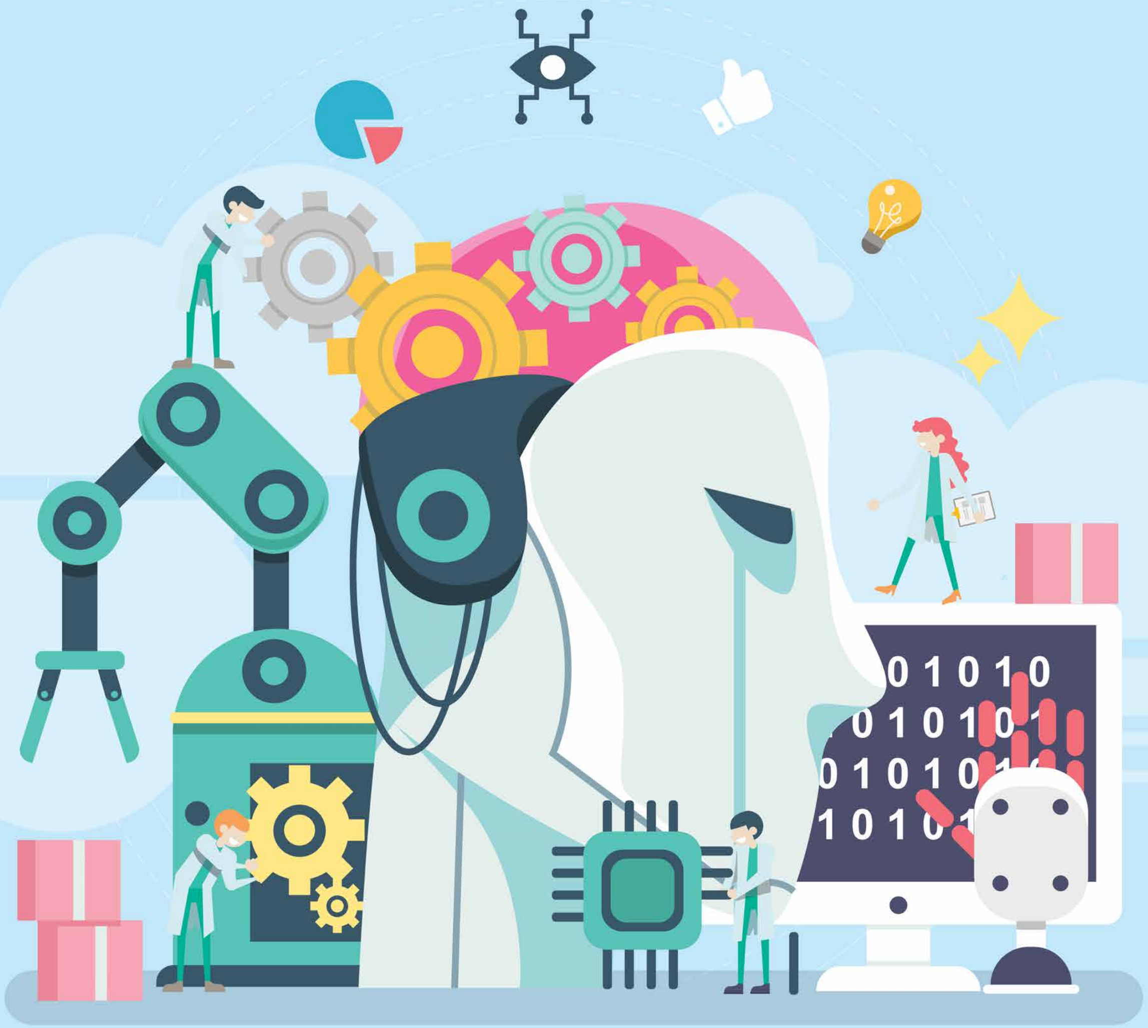

(1) AI (2) ML (3) DL

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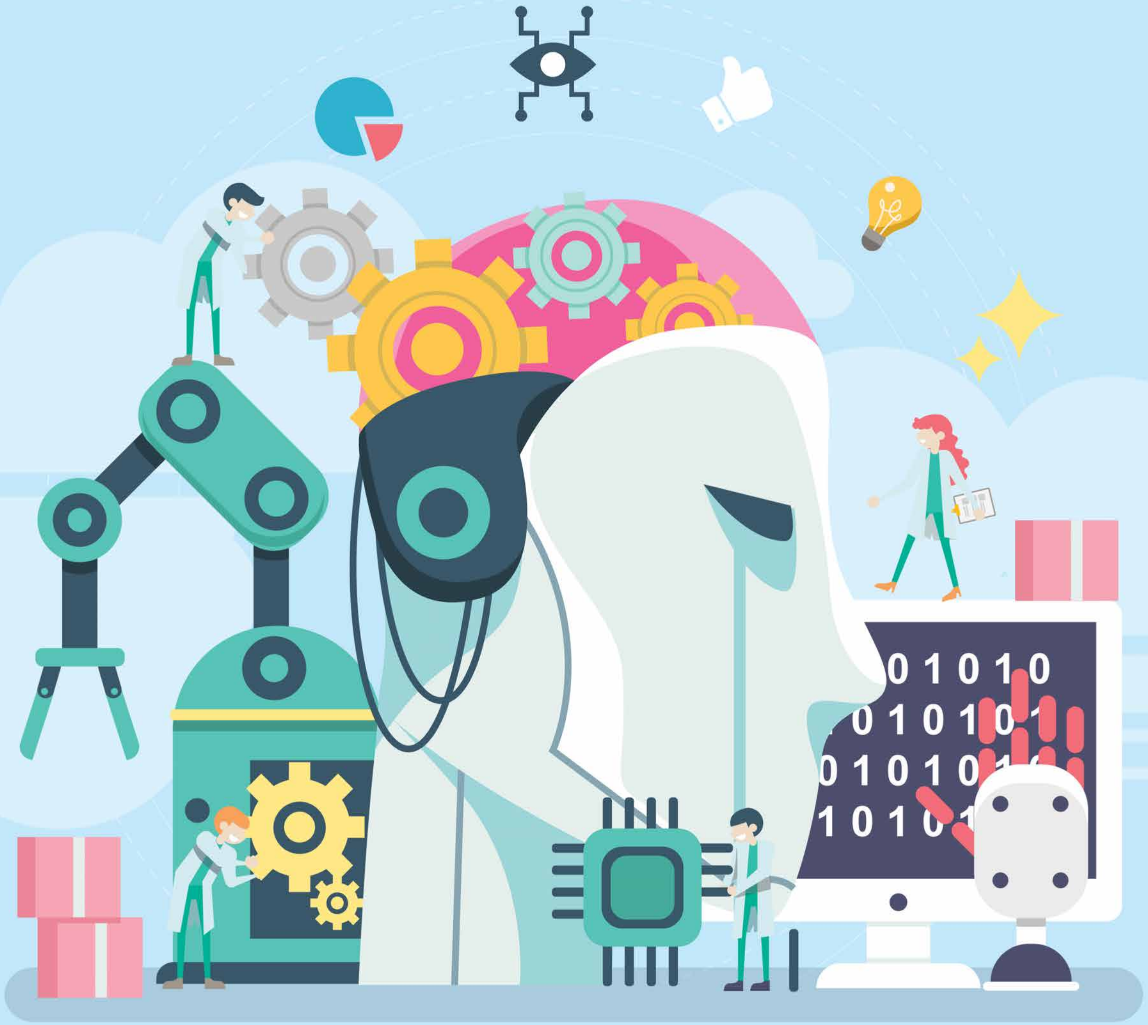


(1) AI (2) ML (3) DL

Future Today Institute: 2019 Trends

2019 Keywords

In our research and modeling for this year's report, a handful of words appeared with significant frequency.

Data
Maps
Regulation
Biotech
China
Monitoring
Listening
Automation
Permissions
Competition
Speaking
Infrastructure
Collaboration
Autonomous
Persistent
Recognition

2019 AI Trends – Future Today Institute

001 Consumer-Grade AI Applications
002 Ubiquitous Digital Assistants
003 A Bigger Role For Ambient Interfaces
004 Deep Linking Everywhere
005 Proliferation of Franken-algorithms
006 Deployable AI Versions of You
007 Ongoing Bias In AI
008 AI Bias Leads To Societal Problems
009 Making AI Explain Itself
010 Accountability and Trust
011 AI Hiding Its Own Data
012 Undocumented AI Accidents on the Rise
013 The AI Cloud
014 Serverless Computing
015 New Kinds of Liability Insurance for AI
016 Generating Virtual Environments From Short Videos
017 AI Spoofing
018 Ambient Surveillance
019 Proprietary, Homegrown AI Languages
020 AI Chipsets
021 Marketplaces For AI Algorithms
022 Even More Consolidation in AI
023 Real-Time Machine Learning
024 Natural Language Understanding (NLU)
025 Machine Reading Comprehension (MRC)
026 Natural Language Generation (NLG)
027 Generative Algorithms For Voice, Sound and Video
028 Real-Time Context in Machine Learning
029 General Reinforcement Learning Algorithm
030 Machine Image Completion
031 Hybrid Human-Computer Vision Analysis
032 Predictive Machine Vision
033 Much Faster Deep Learning
034 Reinforcement Learning and Hierarchical RL
035 Continuous Learning
036 Multitask Learning
037 Generative Adversarial Networks (GANs)
038 New Generative Modeling Techniques
039 Capsule Networks
040 Probabilistic Programming Languages
041 Automated Machine Learning (AutoML)
042 Customized Machine Learning
043 AI For the Creative Process
044 Bots

2019 AI Trends – Future Today Institute

KEY INSIGHT

Artificial Intelligence isn't a trend itself. Artificial intelligence is the most important tech development in our lifetimes. It's not a tech trend; it's the third era of computing. It connects to everything else we do in business, governing and everyday life. We must stop talking about AI as if it will arrive someday in the future. Contrary to a lot of what you've heard, AI is already here. It just didn't show up the way we all expected.

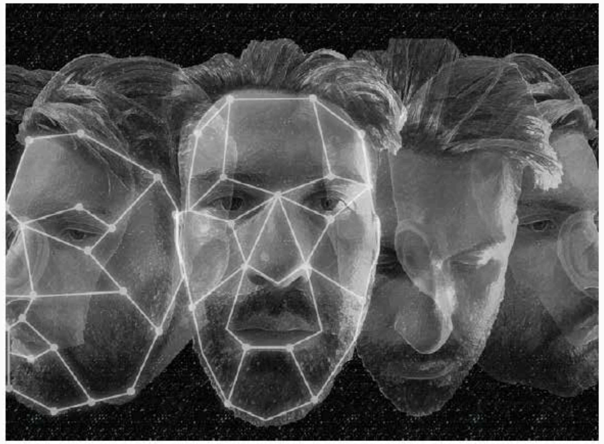
Marvin Minsky, a pioneer in artificial intelligence, often described AI as a "suitcase term." It's a concept that appears simple enough but is actually endlessly complex and packed – like a suitcase – with lots of other ideas, concepts, processes and problems.

Many facets of artificial intelligence (AI) have made our list since we first started publishing this report 12 years ago. Because AI itself isn't the trend, we have identified different themes within AI that you should be following.

2019 AI Trends – Future Today Institute

This moment in time is akin to the few decades when the steam engine gave rise to the Industrial Revolution, and Edison and Westinghouse brought electricity into our homes, offices, schools and factories. For us, AI is that new electricity, but it is our personal data that is generating the current.

2019 AI Trends – Future Today Institute



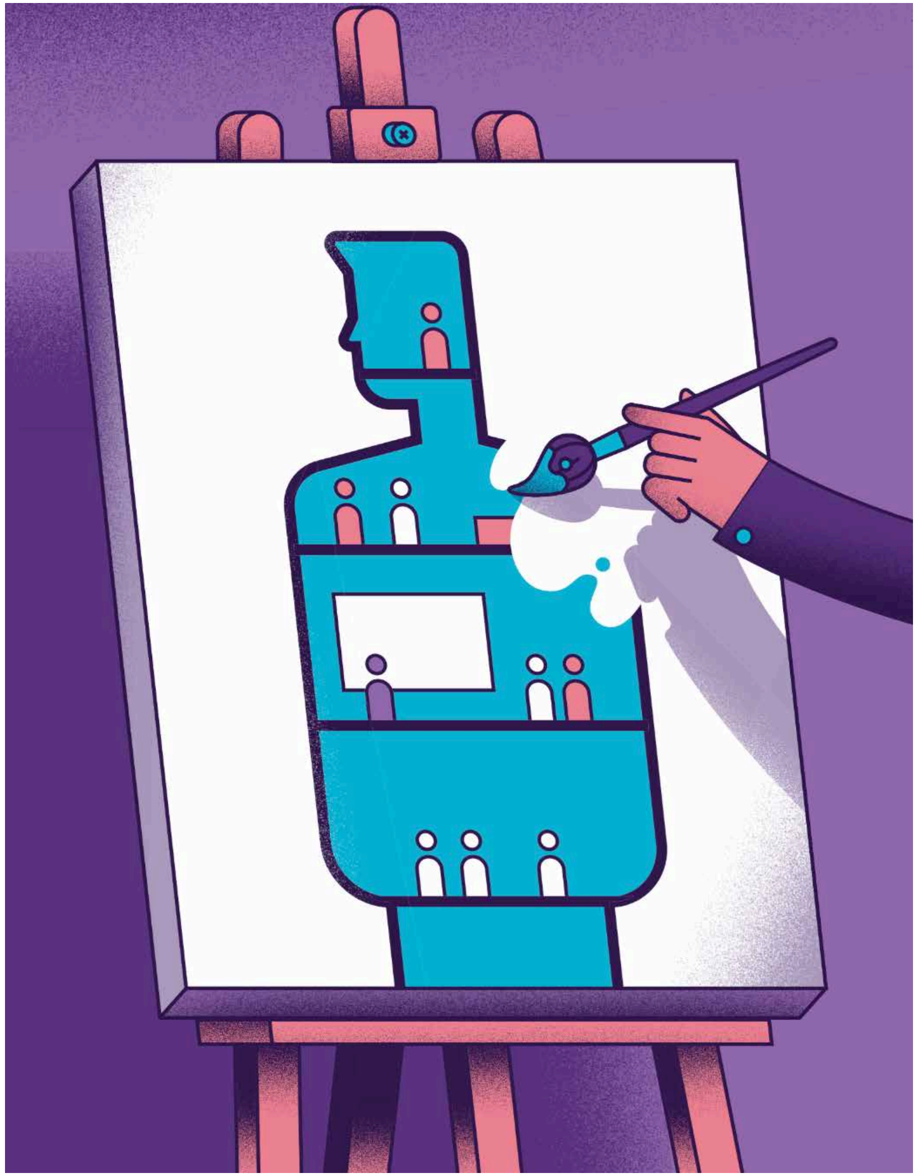
The National Institute of Standards and Technology's Face Recognition Vendor Test–performed in the 2010, 2014 and 2018 evaluations–judged how well an algorithm could match a person's photo with a different one of the same person stored in a large database.

"A strange game. The only winning move is not to play."

– Joshua, in War Games

The CloudSight API is used to recognize real-world objects.

Work 2.0 – Welcome to Super Jobs



Work 2.0 – Welcome to Super Jobs

FIGURE 6

Three domains for reinvention, three approaches to change

	Refresh	Rewire	Recode
Future of the workforce	• Leadership	• Alternative workforce	• Superjobs
Future of the organization	• Human experience • Rewards • Teams		
Future of HR		• Talent access • HR cloud	• Talent mobility • Learning

Source: Deloitte analysis.

Work 2.0 – Welcome to Super Jobs

FIGURE 6

Three domains for reinvention, three approaches to change

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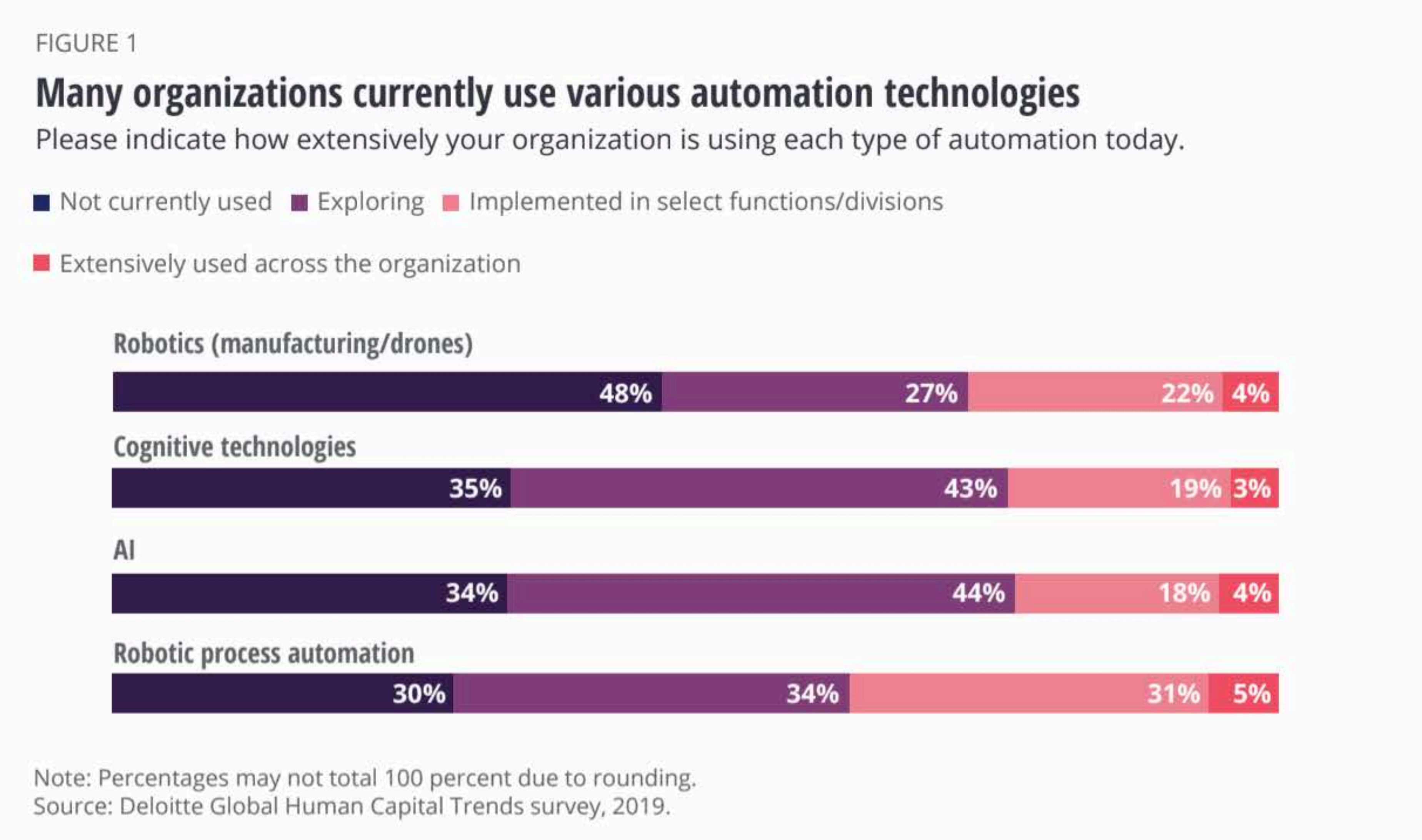


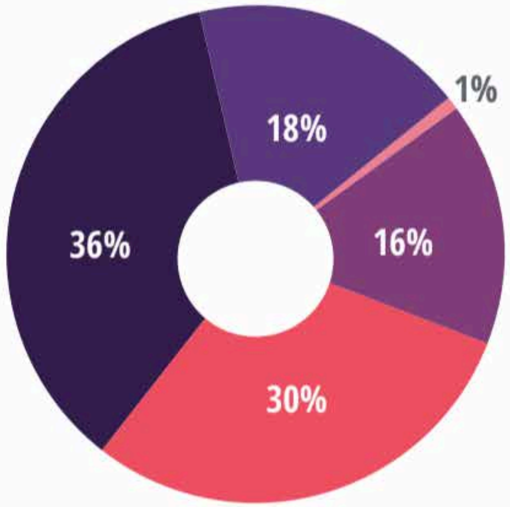
Work 2.0 – Welcome to Super Jobs

FIGURE 2

Many organizations are increasing investments in reskilling their workforce

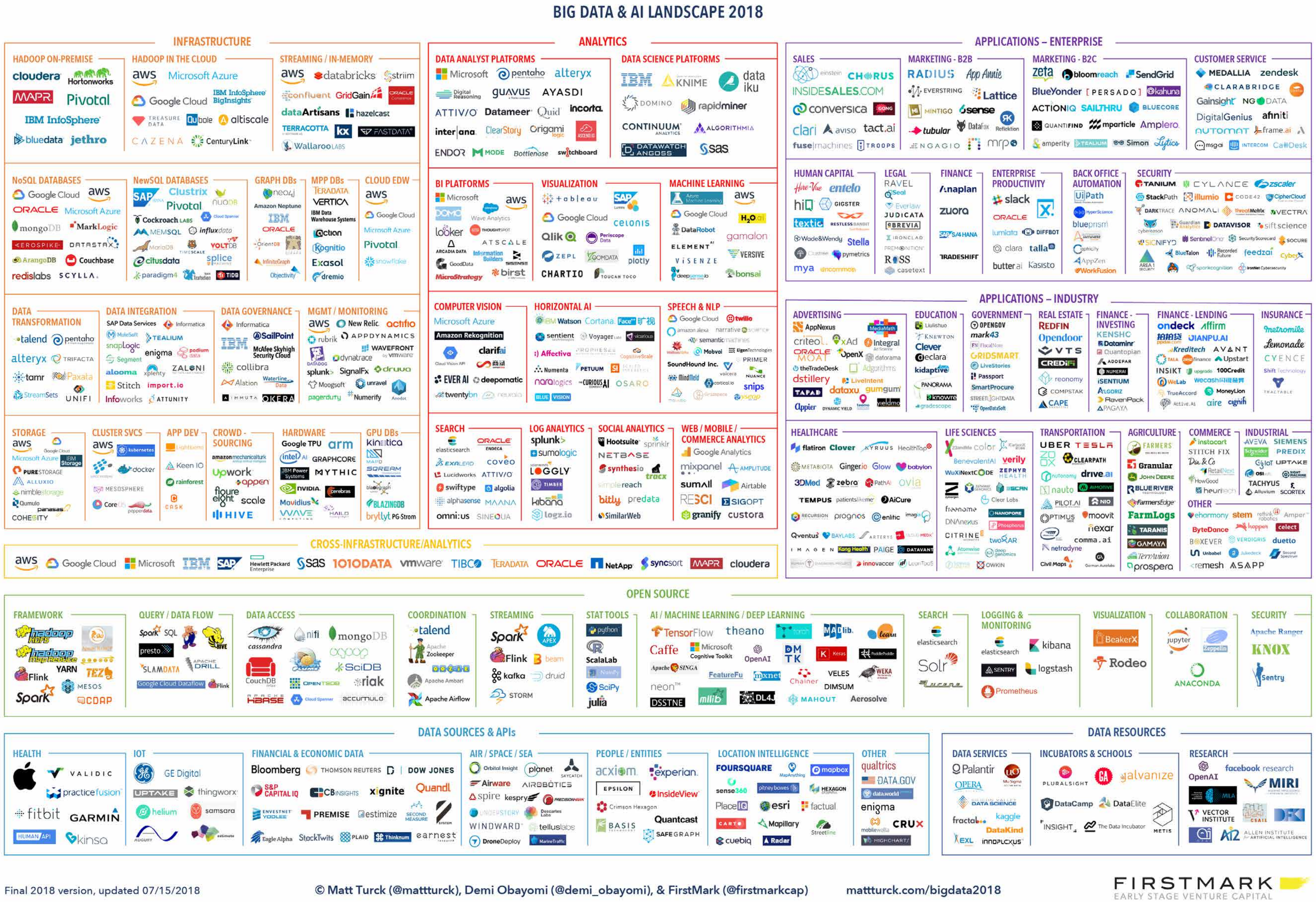
What additional investment are you anticipating to accommodate workforce reskilling?

- Decrease
- Remain the same
- Incremental increase (<5%)
- Moderate increase (6–10%)
- Significant increase (>10%)



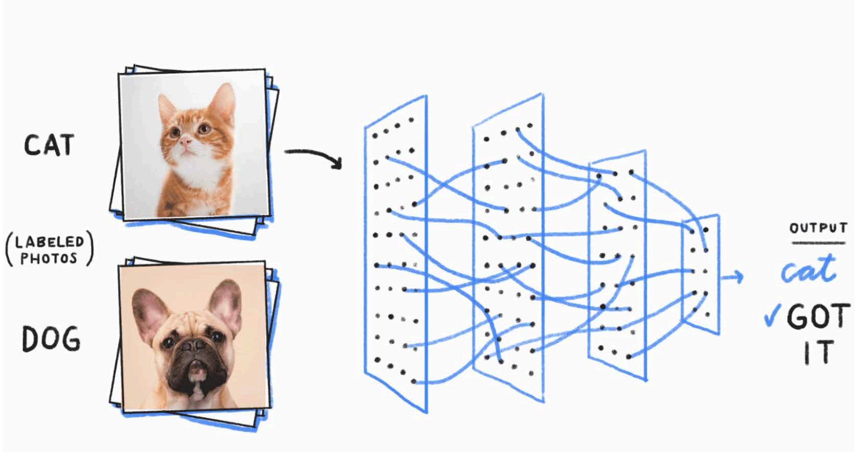
Note: Only respondents who said that automation would require reskilling at their organizations answered this question.
Source: Deloitte Global Human Capital Trends survey, 2019.

Big Data Landscape



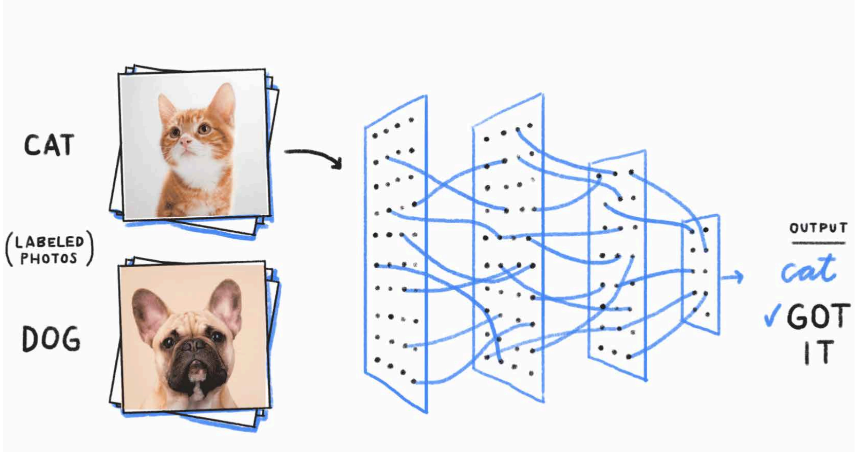
What is Artificial Intelligence?

?



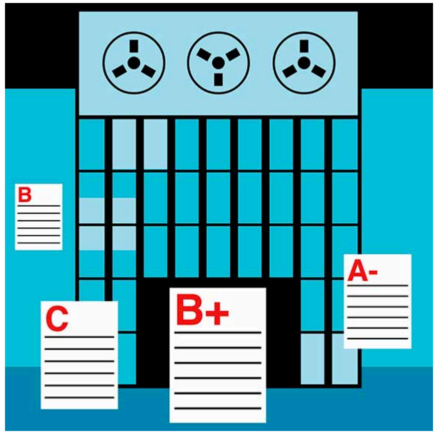
What is Artificial Intelligence?

the theory and development of **computer systems** able to **perform tasks** that **normally require human intelligence**, such as visual perception, speech recognition, decision-making, and translation between languages.



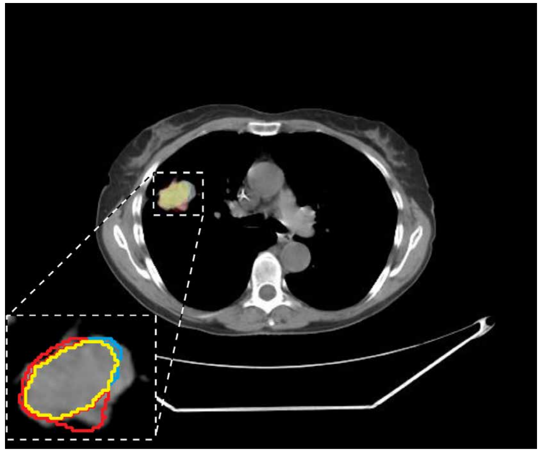
What is Machine Learning?

the process by which a **computer** is able to **improve** its own **performance** by continuously incorporating new data into an existing statistical model



What is Deep Learning?

subset of machine learning in artificial intelligence that has **networks** capable of **learning unsupervised** from **data** that is **unstructured or unlabeled**

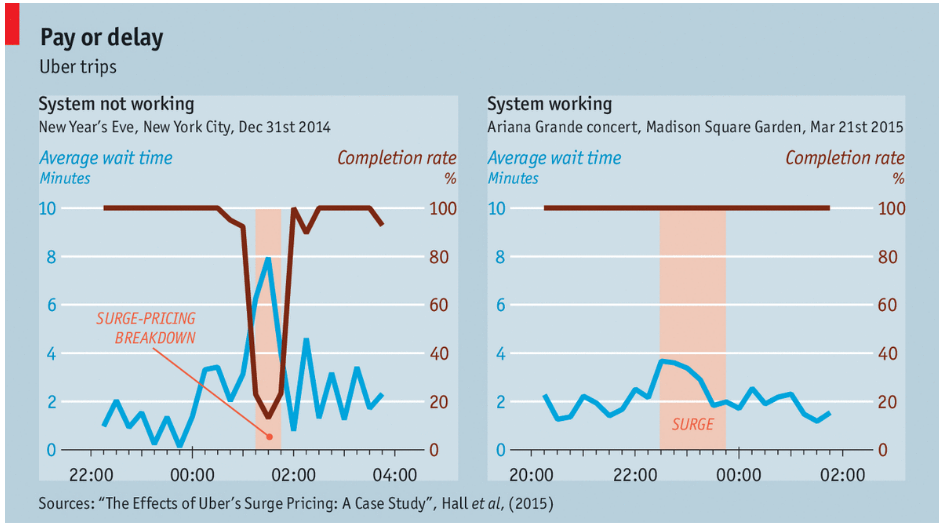


What is Data Science?

multi-disciplinary field that uses **scientific methods**, processes, **algorithms** and systems to **extract** knowledge and **insights** from structured and unstructured **data**.

What is Data Analysis?

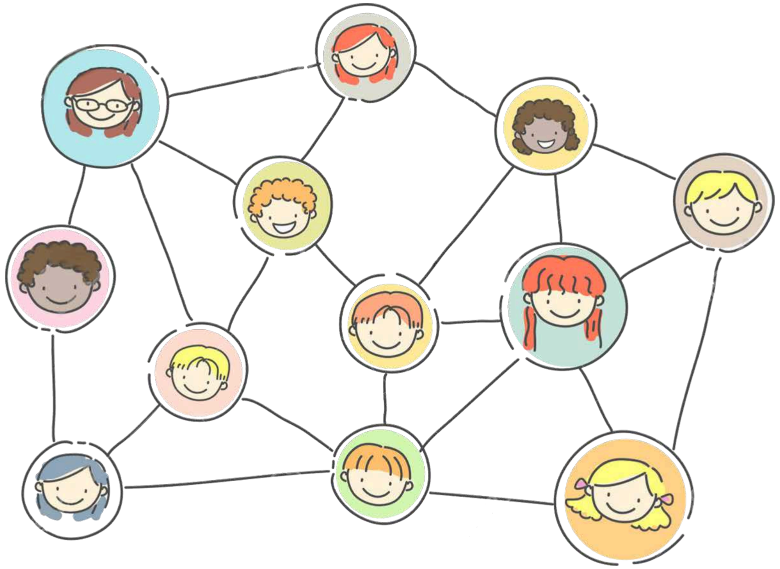
process of **inspecting, cleansing, transforming, and modeling** data with the goal of discovering useful information, **informing conclusions**, and supporting decision-making



Economist.com

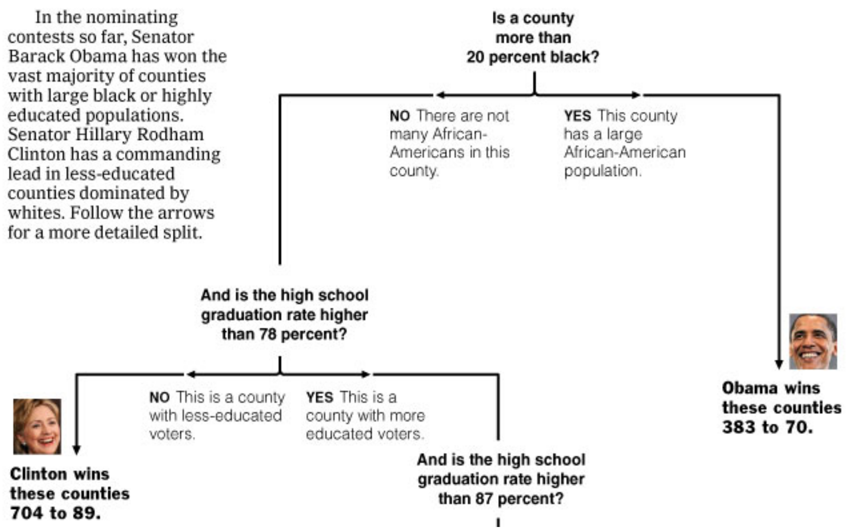
What is Data Mining?

process of **discovering patterns** in large data sets involving methods at the intersection of **machine learning**, **statistics**, and **database systems**



What are Algorithms?

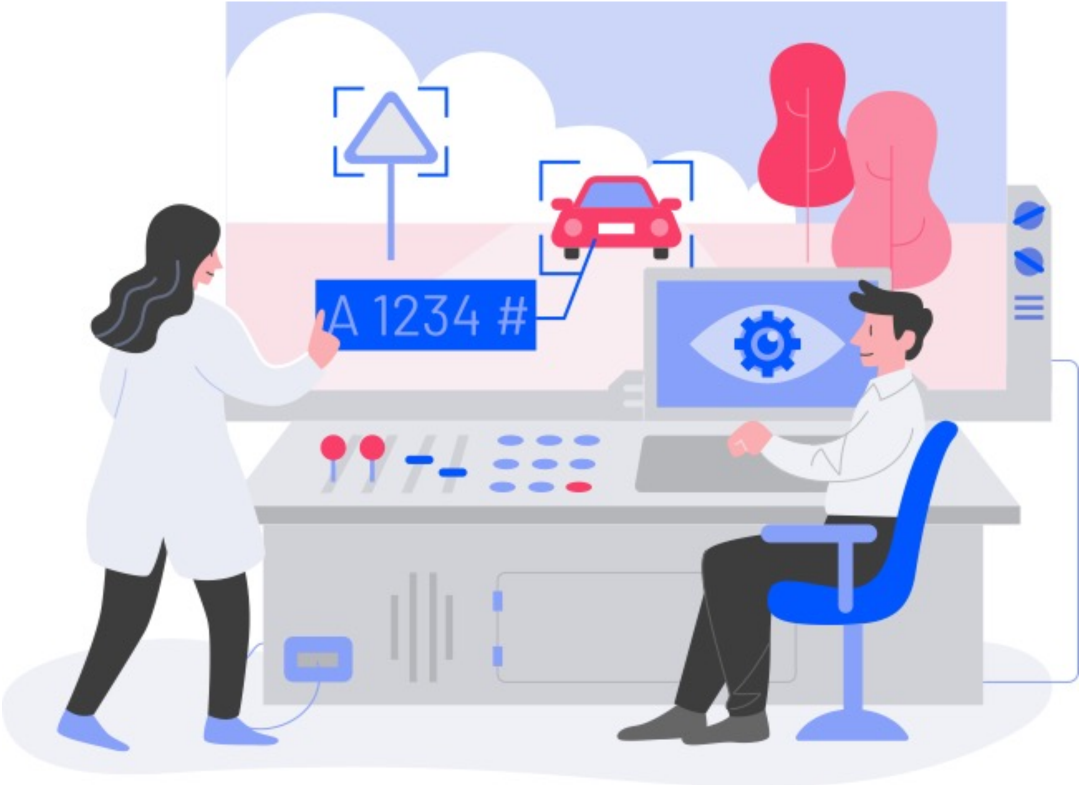
a procedure for **solving** a **mathematical problem** in a finite number of steps that frequently **involves repetition** of an **operation**



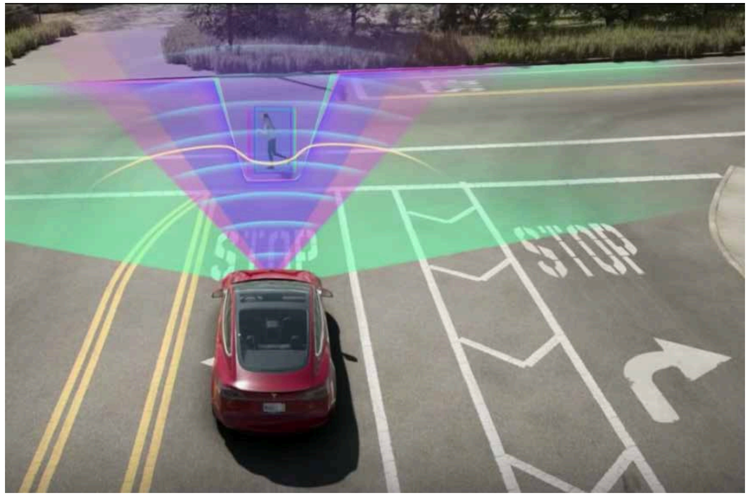
What is a Neural Network?

a computer architecture in which a number of **processors** are **interconnected** in a manner suggestive of the connections between neurons in a human brain and which is able to **learn** by a process of **trial and error**

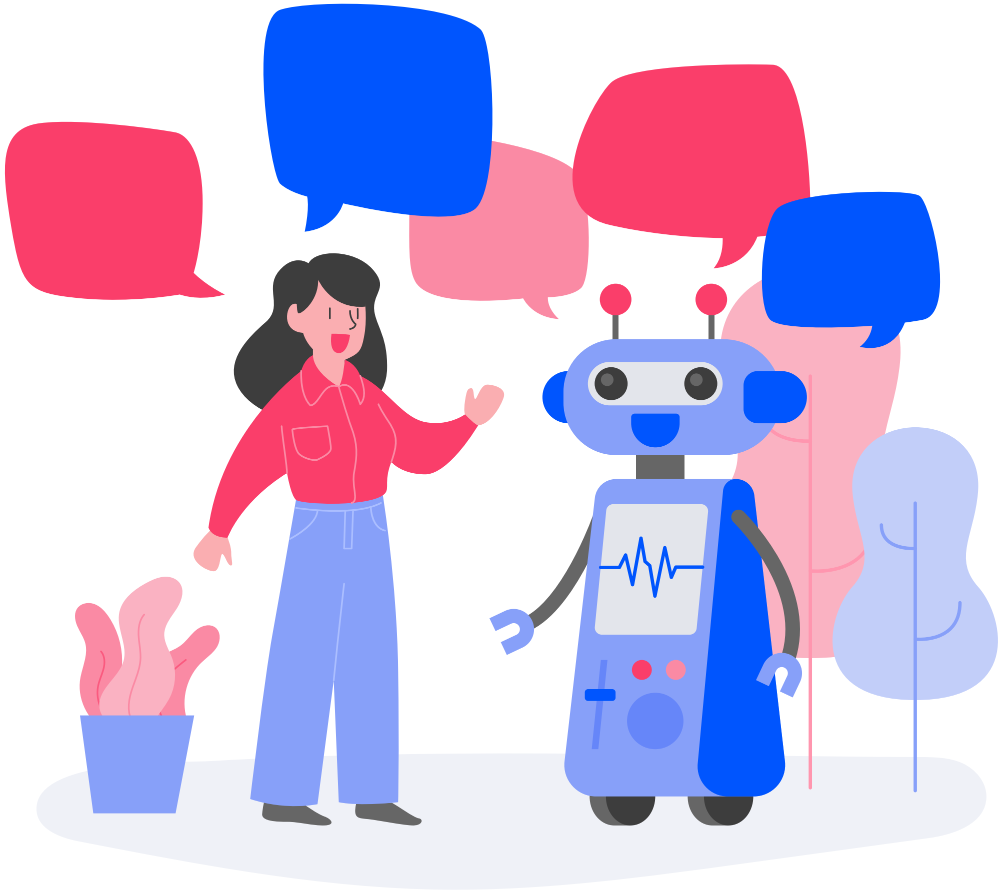
What is Computer Vision?



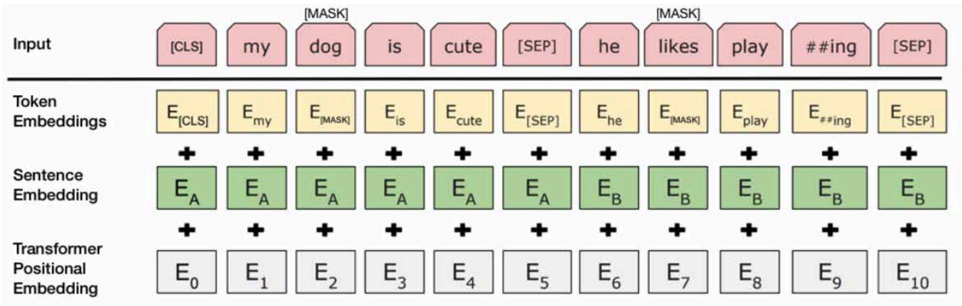
interdisciplinary scientific field that deals with how **computers** can be made to **gain** high-level **understanding** from digital **images or videos**



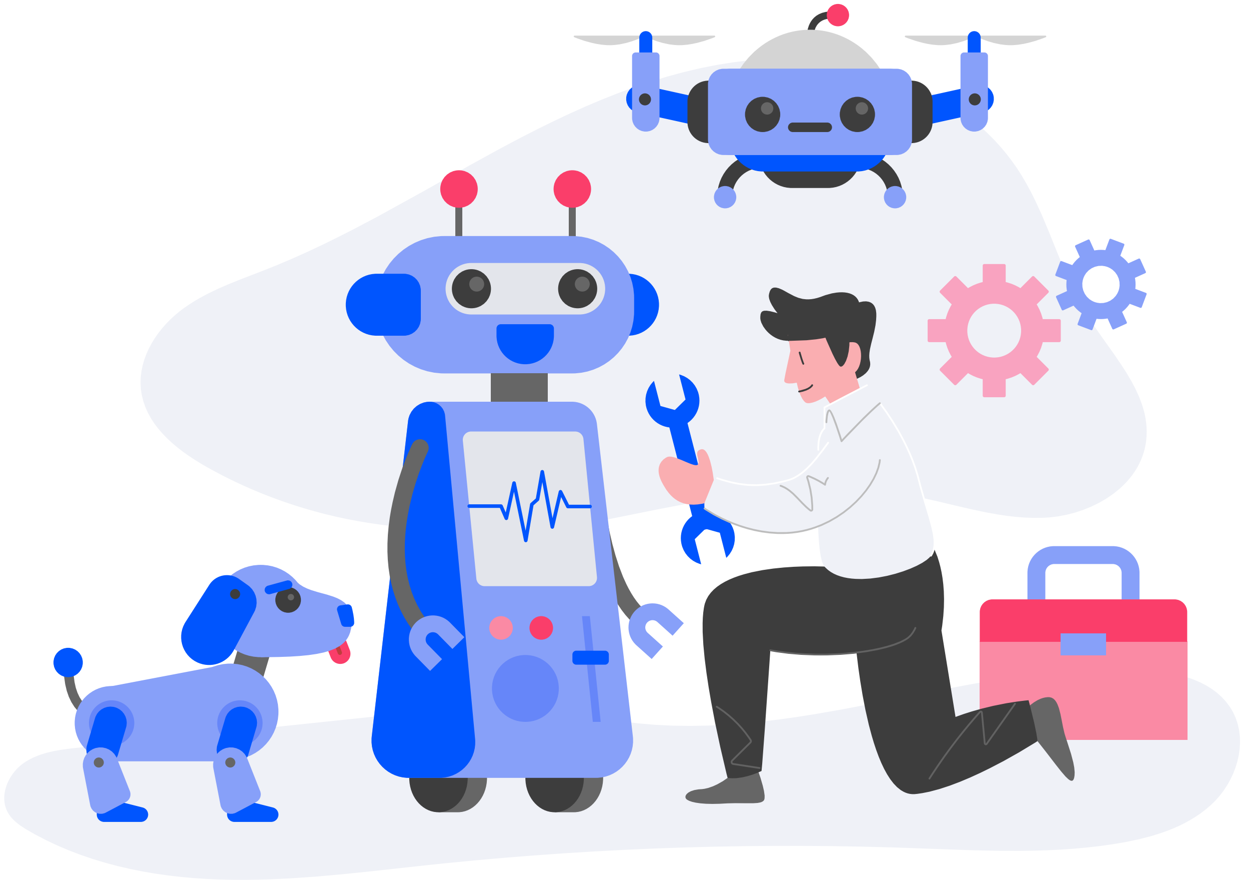
What is Natural Language Processing?



subfield of computer science, information engineering, and artificial intelligence concerned with the **interactions** between **computers** and **human (natural) languages**, in particular how to program computers to process and **analyze** large amounts of **natural language data**



What is Robotics Engineering?



behind-the-scenes **design of robotic systems** that are able to **perform duties** that **humans** are either **unable or prefer not to complete**

Common Language: Data Science Workflow

01

Identify the problem

What is the challenge you would like to solve? What is the hypothesis and critical goals for success?

02

Acquire the data

Identify the right data sets and tools to work with. Read documentation and review the data.

03

Refine the data

Clean the data and add calculations to better explain and understand your data.

04

Build data models

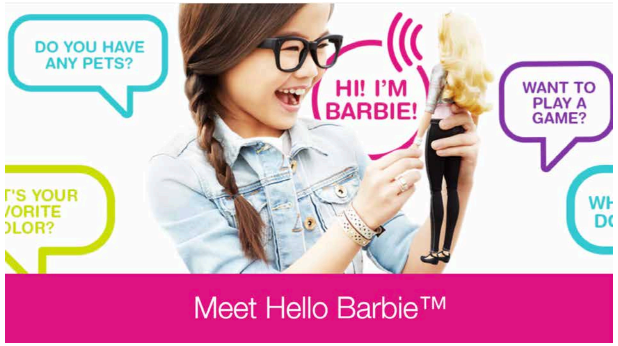
Whether visualizations, or data science models, explore the insights and trends that you can reveal from your data.

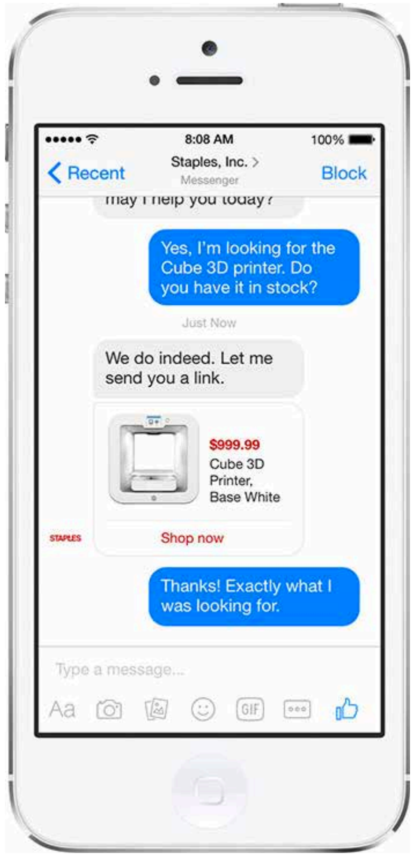
05

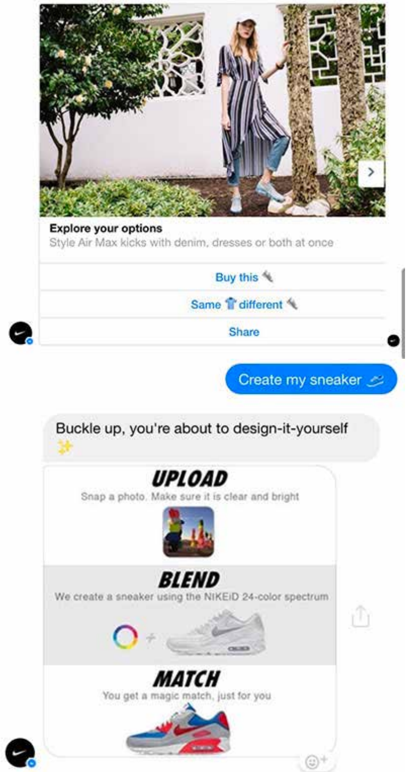
Communicate your results

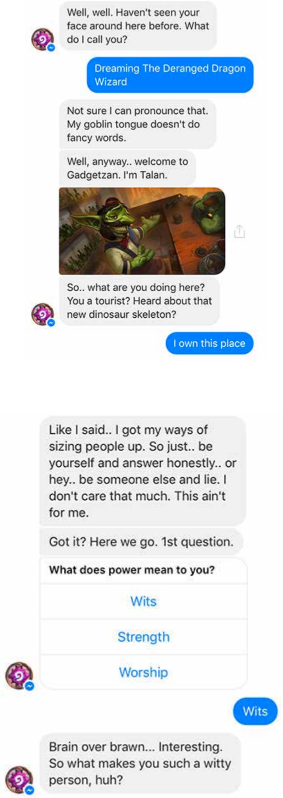
Create a dashboard, a report, presentation, or machine learning pipeline to share the outcomes with both your internal and external stakeholders

Chat Bots: A Use Case in Conversational AI









Brainstorming: Individual Exercise

What challenges are your organization experiencing?

Brainstorming: IRT Scoring (1 to 10)

How impactful will this challenge be to your organization and community?

How much will this improve your organizational readiness?

How time sensitive is this goal for your organization to achieve in the next 6 months?

Brainstorming: Rank your challenges

Add all 3 numbers.

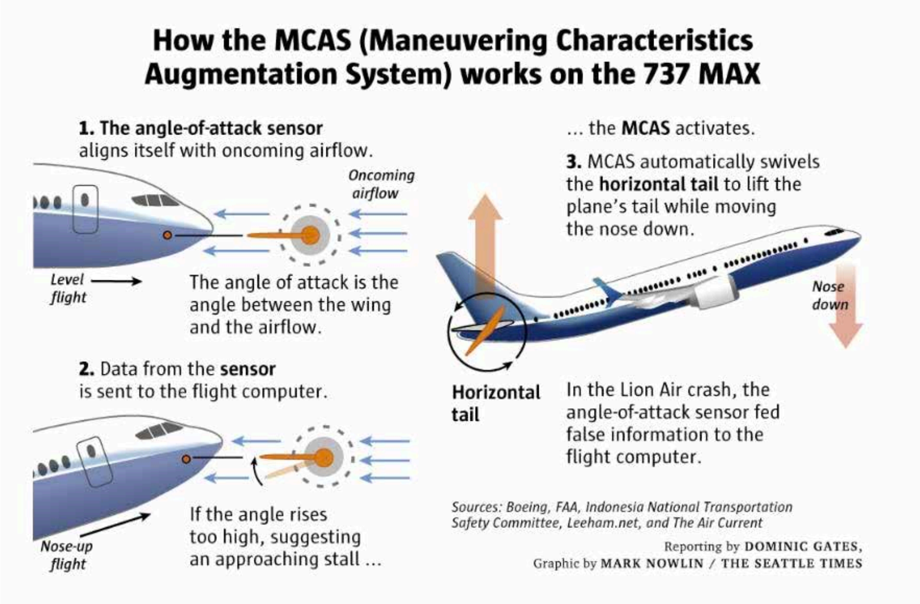
Which ranked the highest?

How close was second?

Third?

Brainstorming: SMART Goals: Independent

Specific: What will you accomplish?
Measurable: By how much will you increase?
Actionable: With what method will you grow?
Realistic: How plausible is this goal to achieve?
Timely: By when will you accomplish this goal?



Reduce manufacturing defects.

Vs.

By November 2, 2019, shorten the faulty reading rates for AOA sensors by 15% for Boeing 737 MAX aircraft through piloting design implementations.

Brainstorming: SMART Goals: **Group** Share

Specific:	What will you accomplish?
Measurable:	By how much will you increase?
Actionable:	With what method will you grow?
Realistic:	How plausible is this goal to achieve?
Timely:	By when will you accomplish this goal?

Your SMART Goal

Common Language: Data Science Workflow

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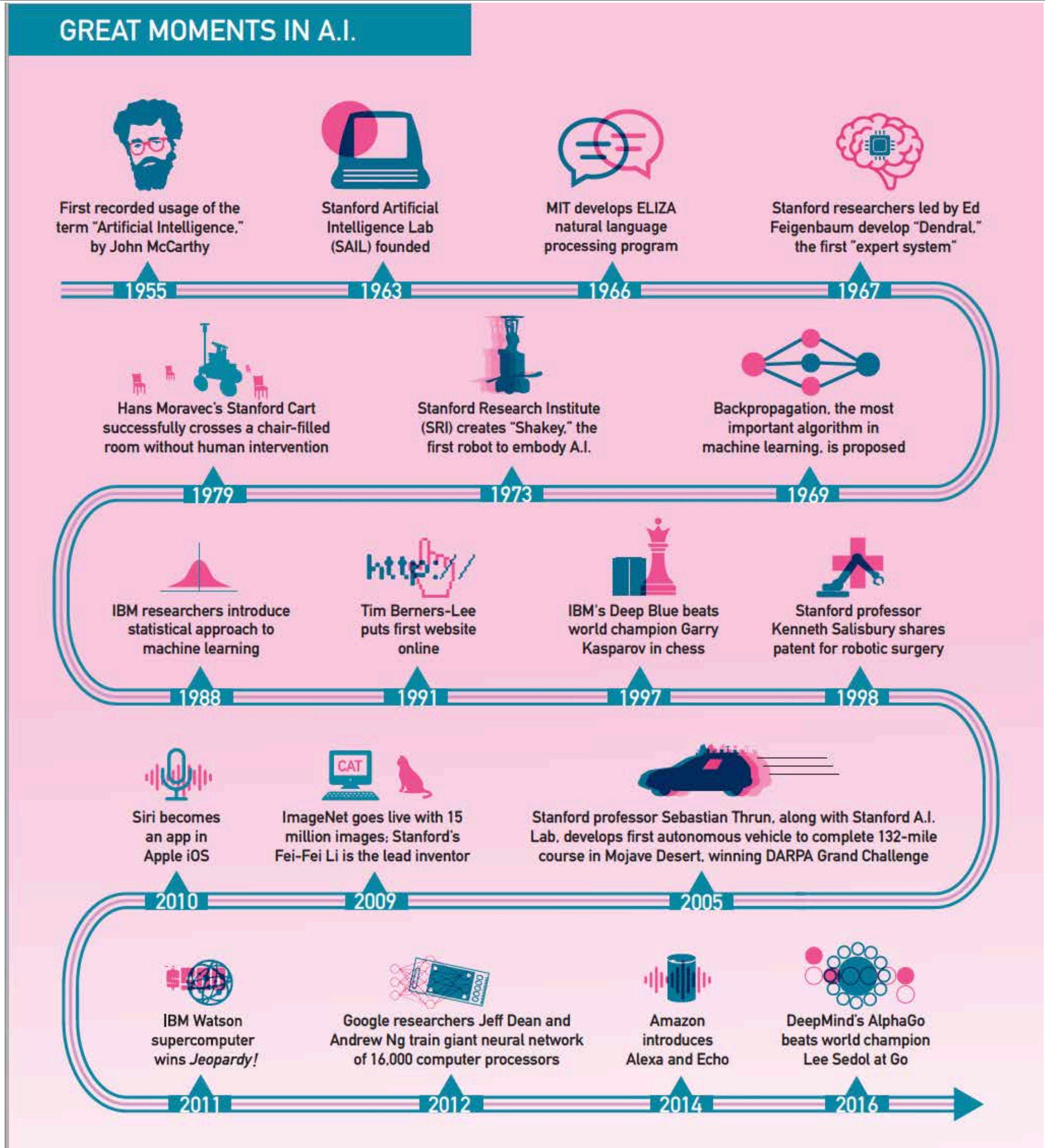
Discover: Explore Data Sets

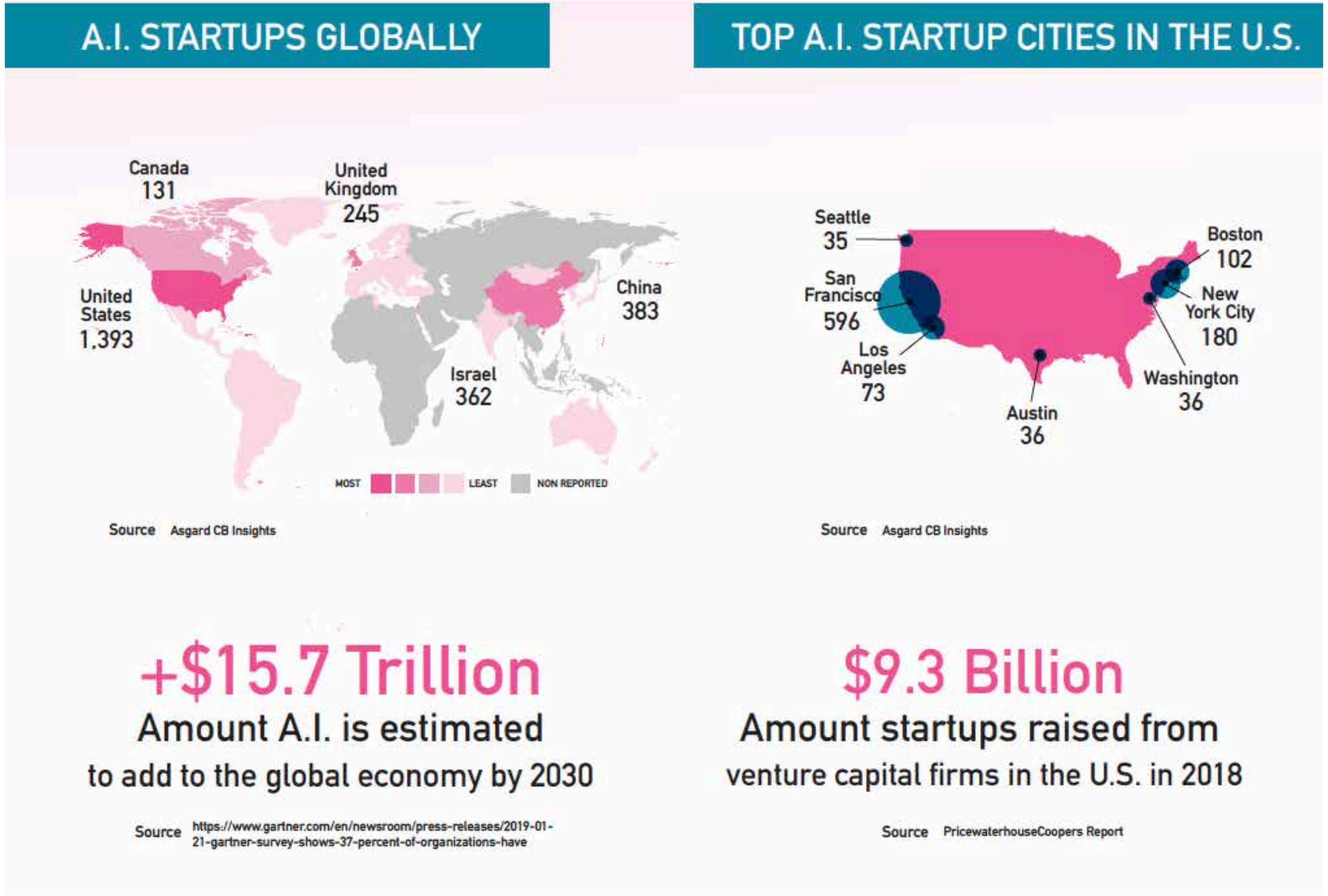
Scan me

bit.ly/opendatasets

A brief history on AI



AI Landscape



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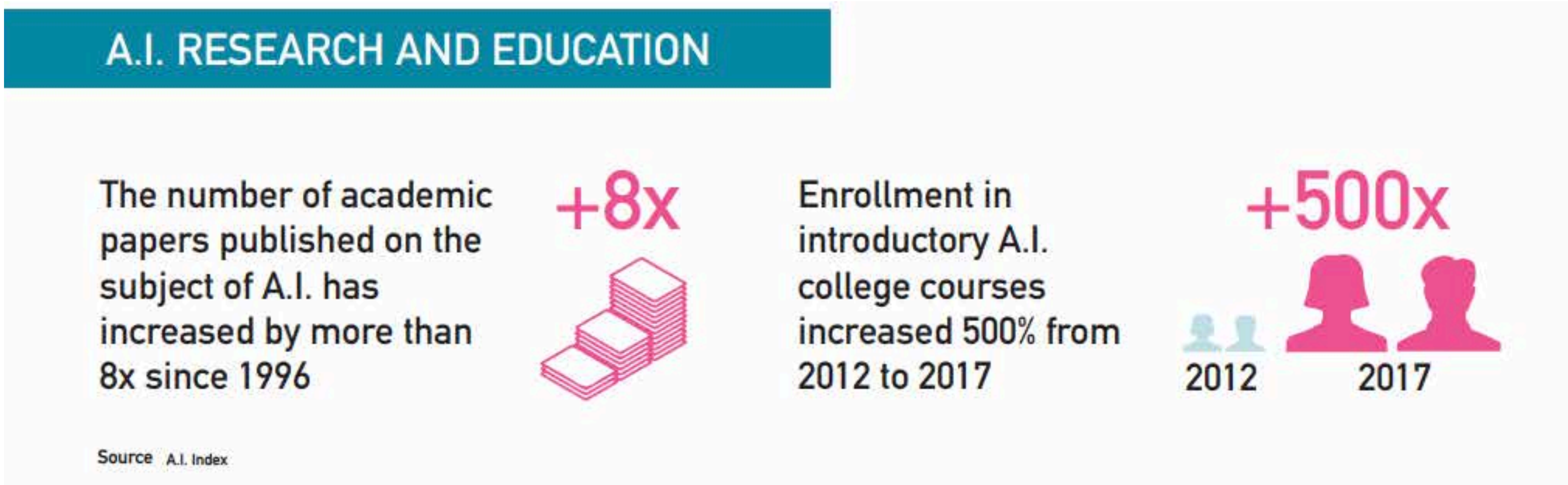

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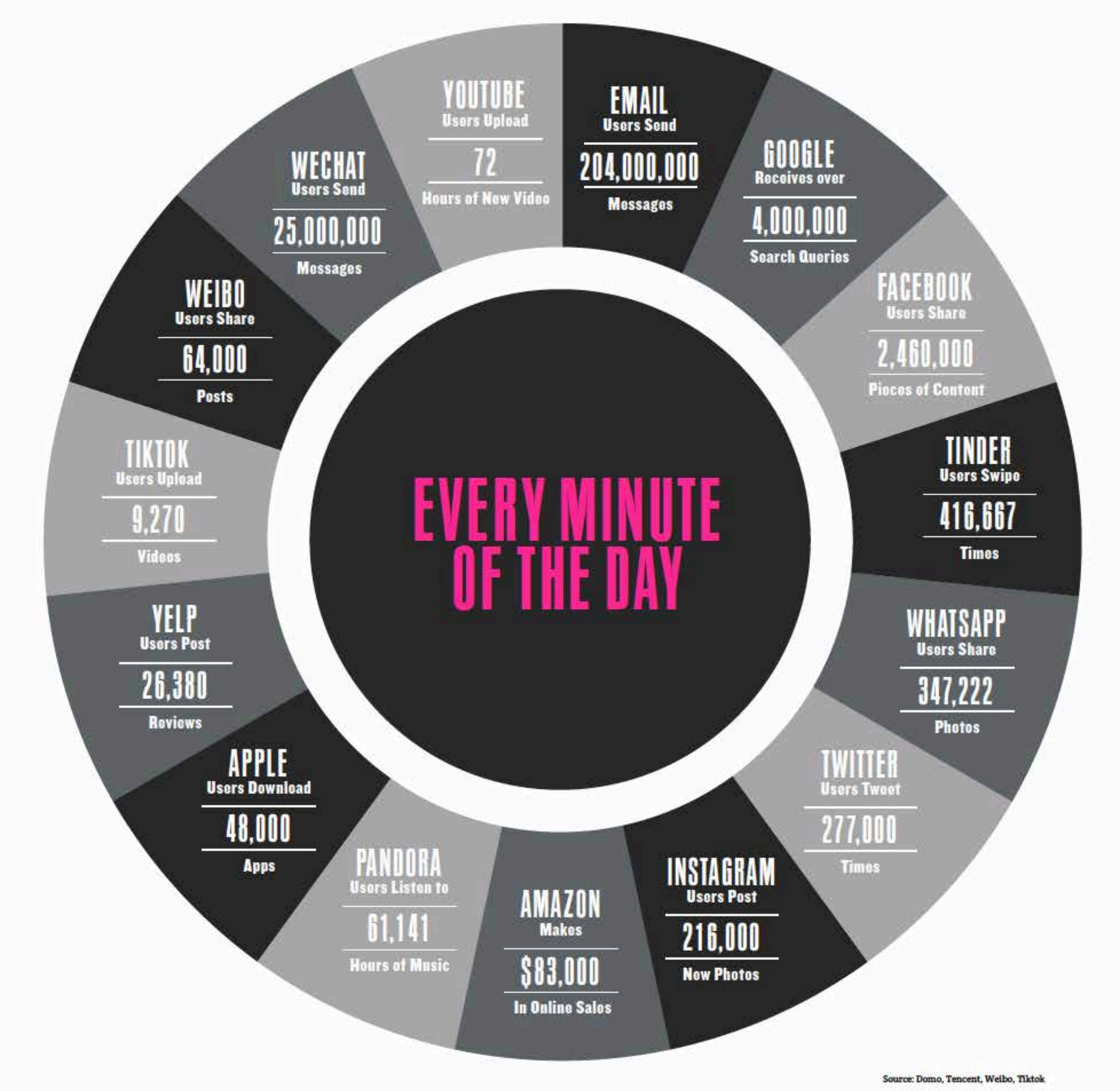
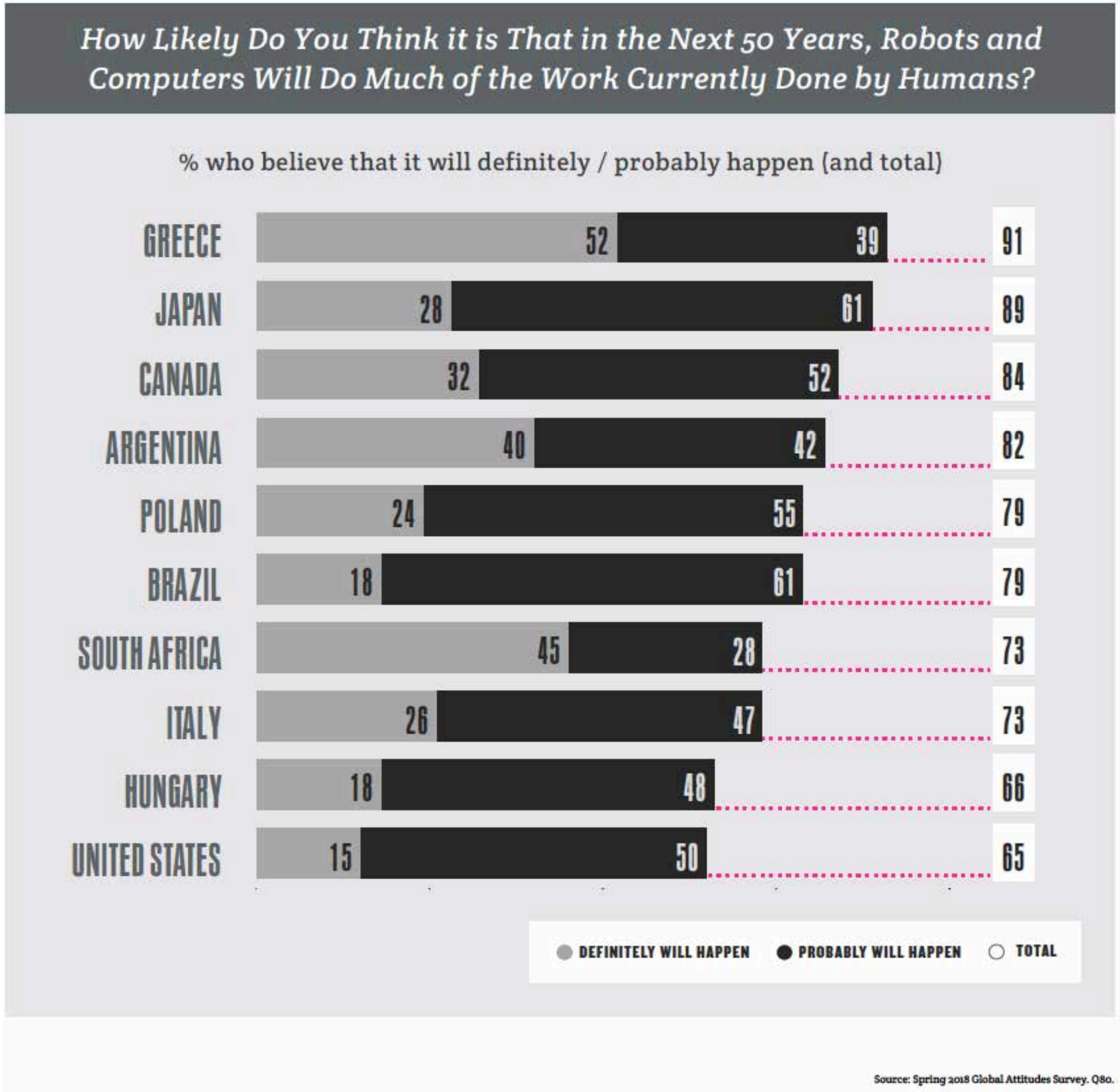


AI Landscape

In January, the EU Parliament debated a new legal status for robots as "electronic persons." Courts in Argentina, Colombia and India recognize apes and bears as having certain rights, such as habeas corpus. Courts in New Zealand, Ecuador and Colombia have extended the status of rights-bearing person to nature herself.

"Beyond the 'Human' in Human Rights: The Universal Declaration at 70"
Scientific American

AI Landscape



Common Language: Training the Model

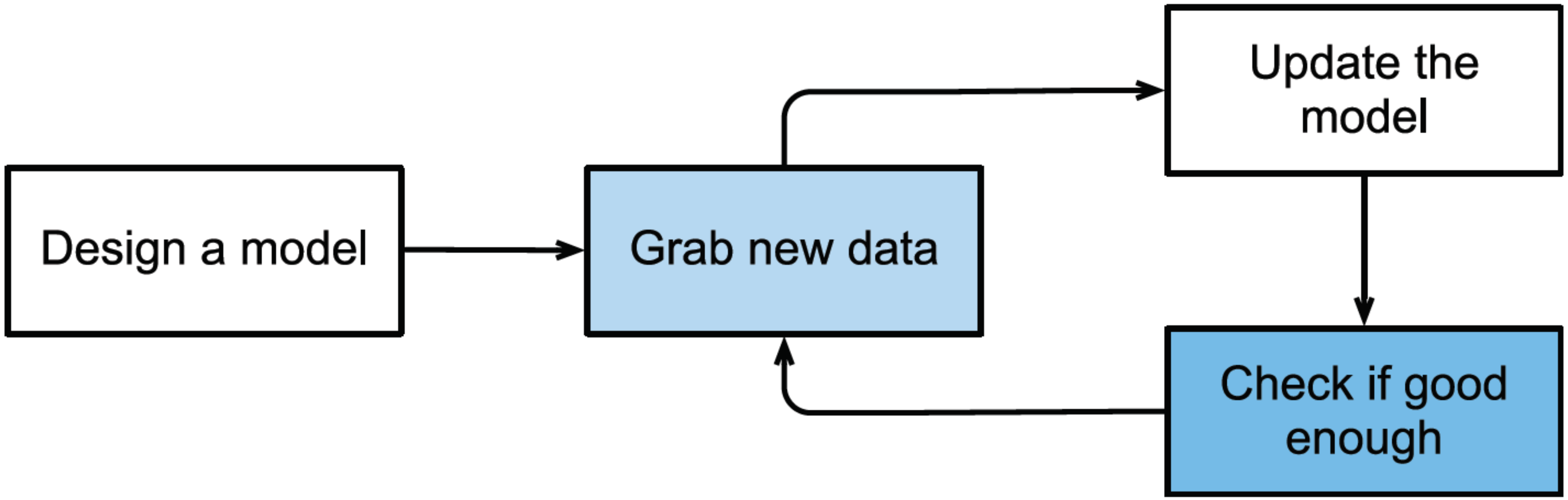


Fig. 3.1.2: A typical training process.

Common Language: Algorithms

BASIC REGRESSION

LINEAR
linear_model.LinearRegression()
Lots of numerical data

LOGISTIC
linear_model.LogisticRegression()
Target variable is categorical

CLASSIFICATION

NEURAL NET
neural_network.MLPClassifier()
Complex relationships. Prone to overfitting
Basically magic.

K-NN
neighbors.KNeighborsClassifier()
Group membership based on proximity

DECISION TREE
tree.DecisionTreeClassifier()
If/then/else. Non-contiguous data.
Can also be regression.

RANDOM FOREST
ensemble.RandomForestClassifier()
Find best split randomly
Can also be regression

SVM
svm.SVC() svm.LinearSVC()
Maximum margin classifier. Fundamental
Data Science algorithm

NAIVE BAYES
GaussianNB() MultinominalNB() BernoulliNB()
Updating knowledge step by step
with new info

CLUSTER ANALYSIS

K-MEANS
cluster.KMeans()
Similar datum into groups based
on centroids

ANOMALY DETECTION
covariance.EllipticalEnvelope()
Finding outliers through grouping

Common Language: Supervised Learning

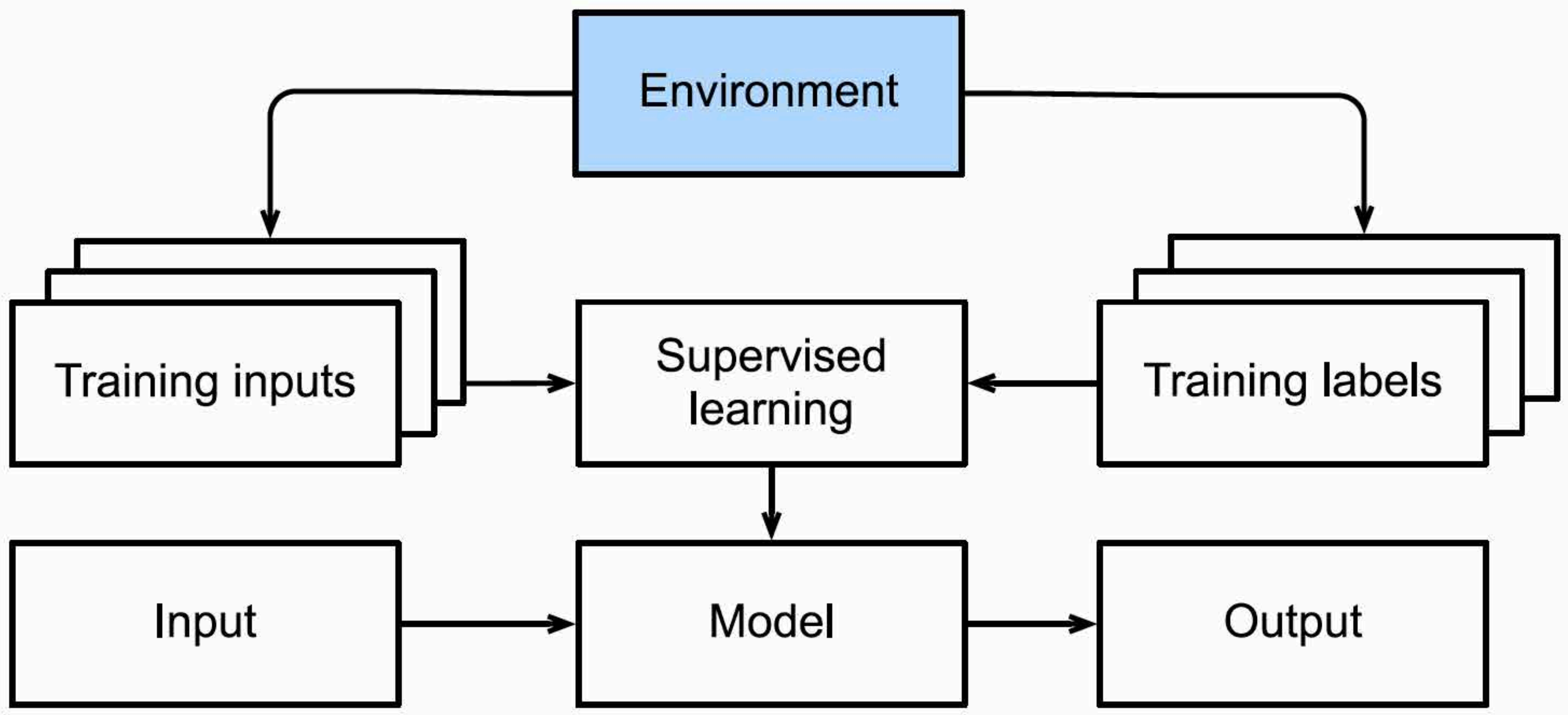
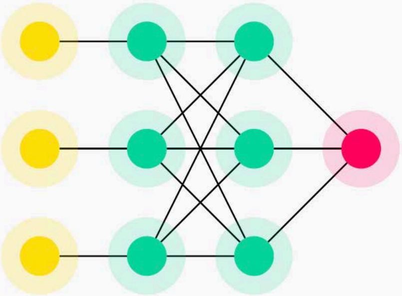


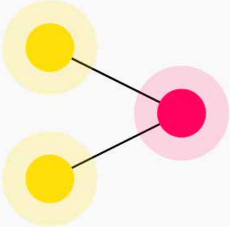
Fig. 3.3.7: Collect data for supervised learning from an environment.

Common Language: Neural Networks

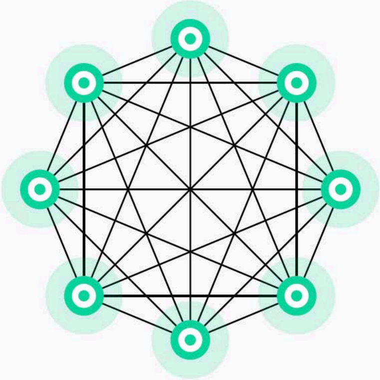
Support Vector Machine **(SVM)**



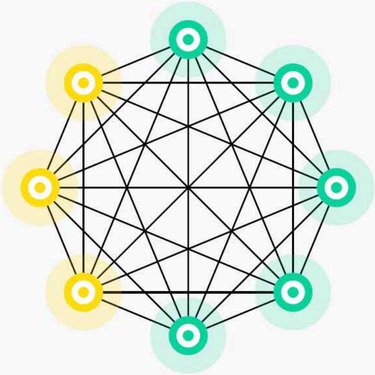
Perceptron **(P)**



Markov Chain **(MC)**



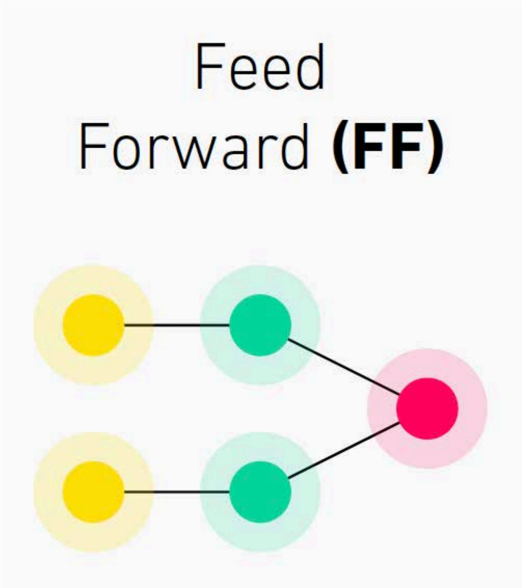
Boltzman Machine **(BM)**

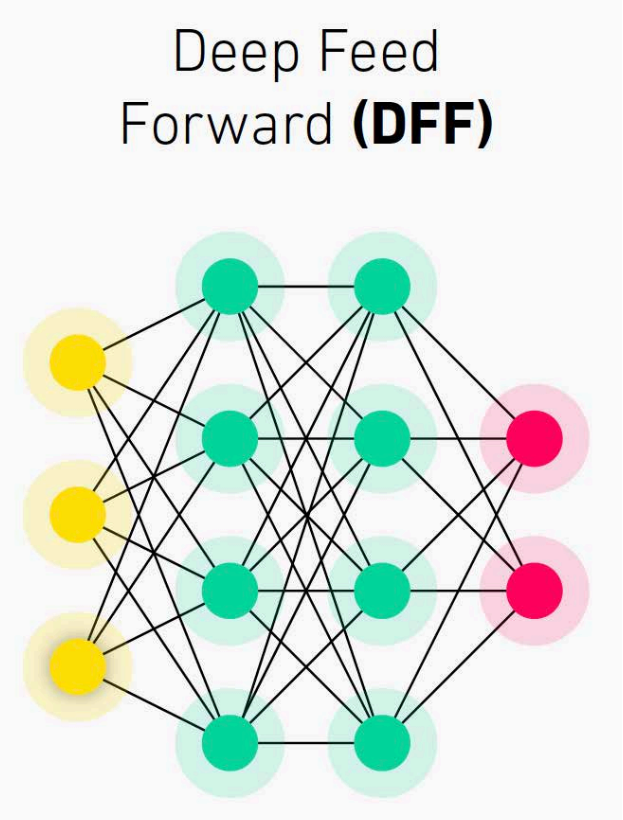


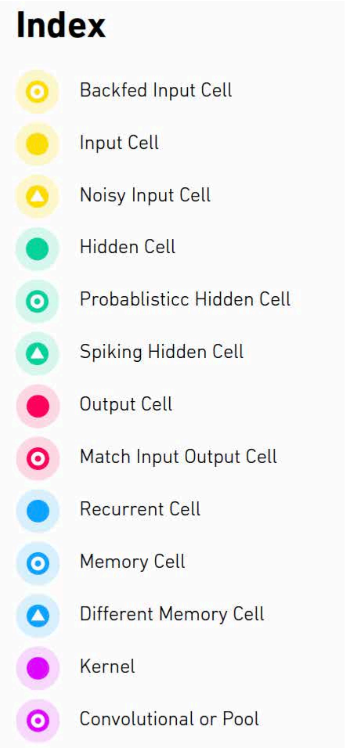
Index

- Backfed Input Cell
- Input Cell
- Noisy Input Cell
- Hidden Cell
- Probablisticc Hidden Cell
- Spiking Hidden Cell
- Output Cell
- Match Input Output Cell
- Recurrent Cell
- Memory Cell
- Different Memory Cell
- Kernel
- Convolutional or Pool

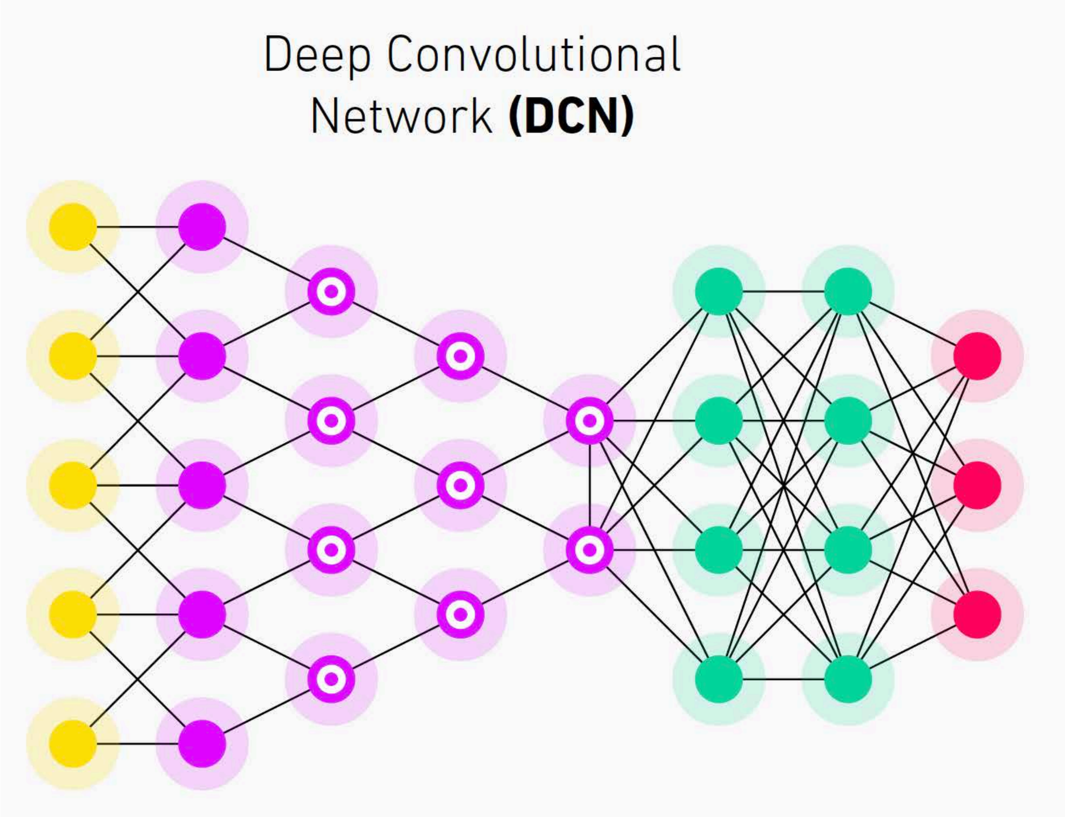
Common Language: Neural Networks

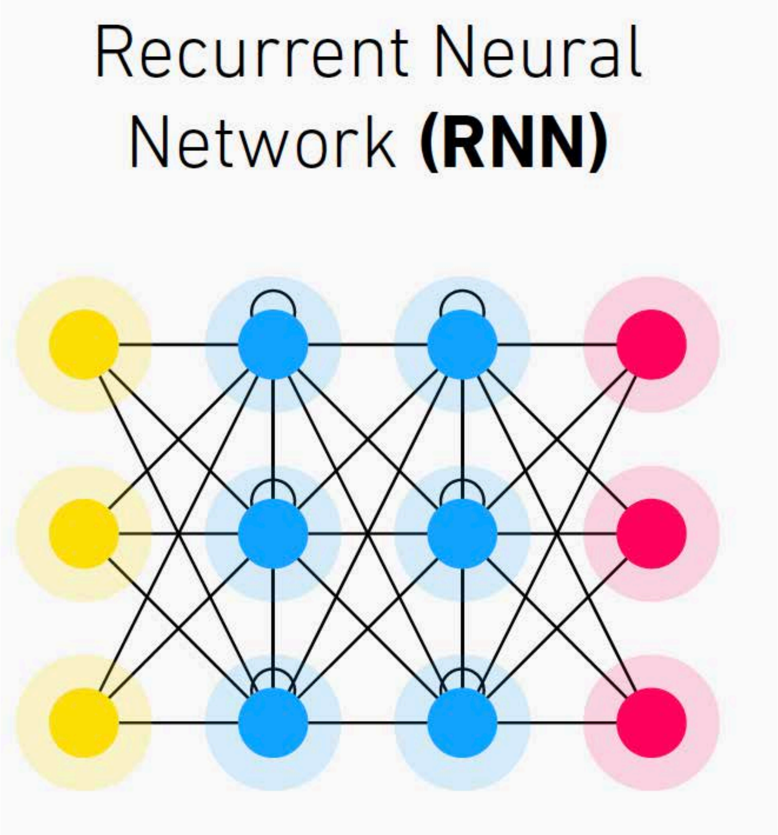






Common Language: Neural Networks





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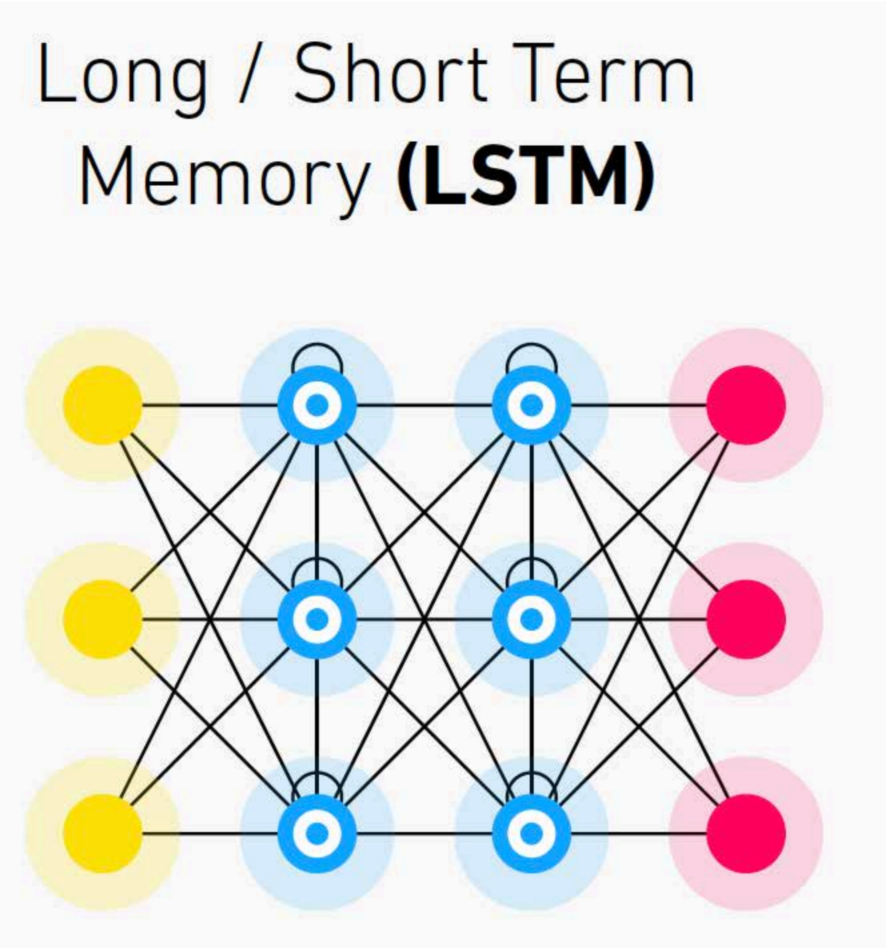
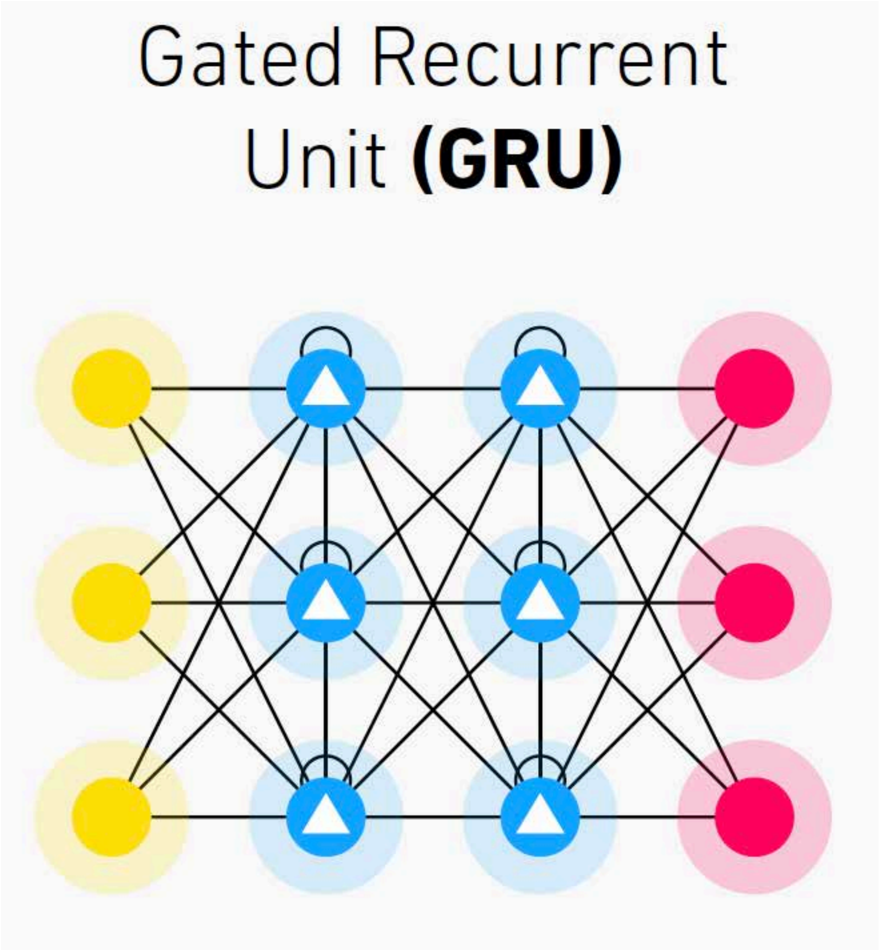
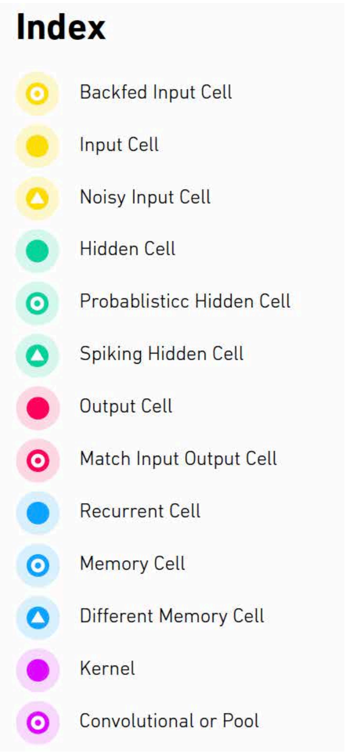
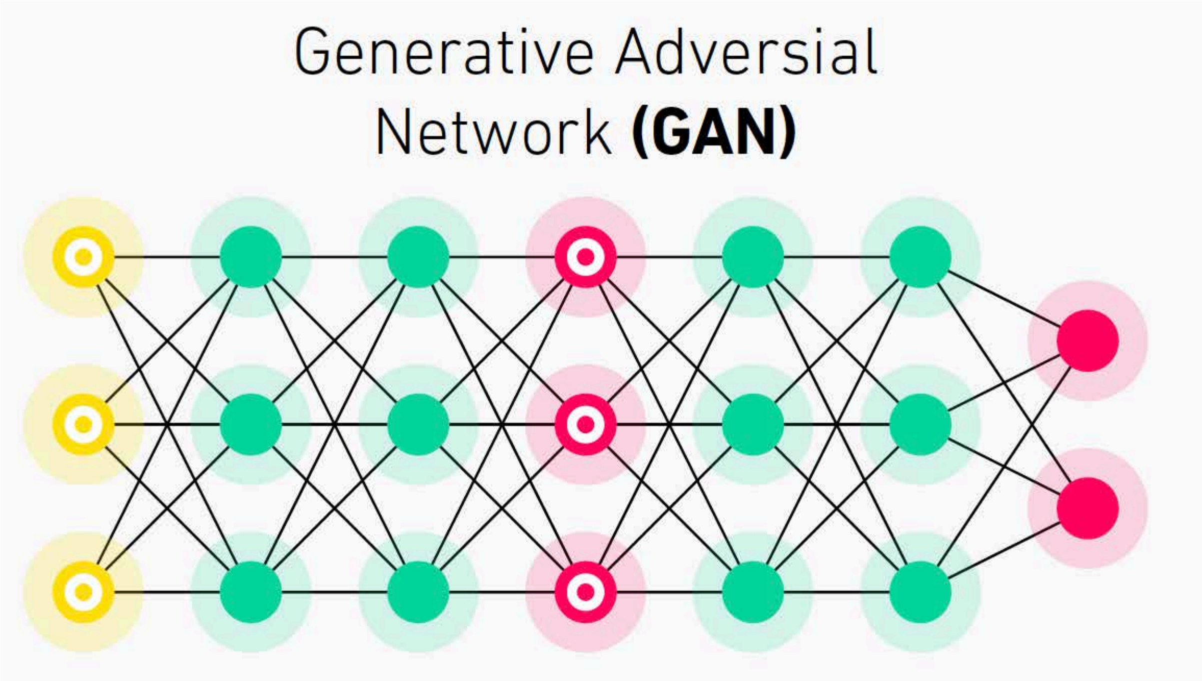






Common Language: Neural Networks



Index

- Backfed Input Cell
- Input Cell
- Noisy Input Cell
- Hidden Cell
- Probablisticc Hidden Cell
- Spiking Hidden Cell
- Output Cell
- Match Input Output Cell
- Recurrent Cell
- Memory Cell
- Different Memory Cell
- Kernel
- Convolutional or Pool

Common Language: Reinforced Learning

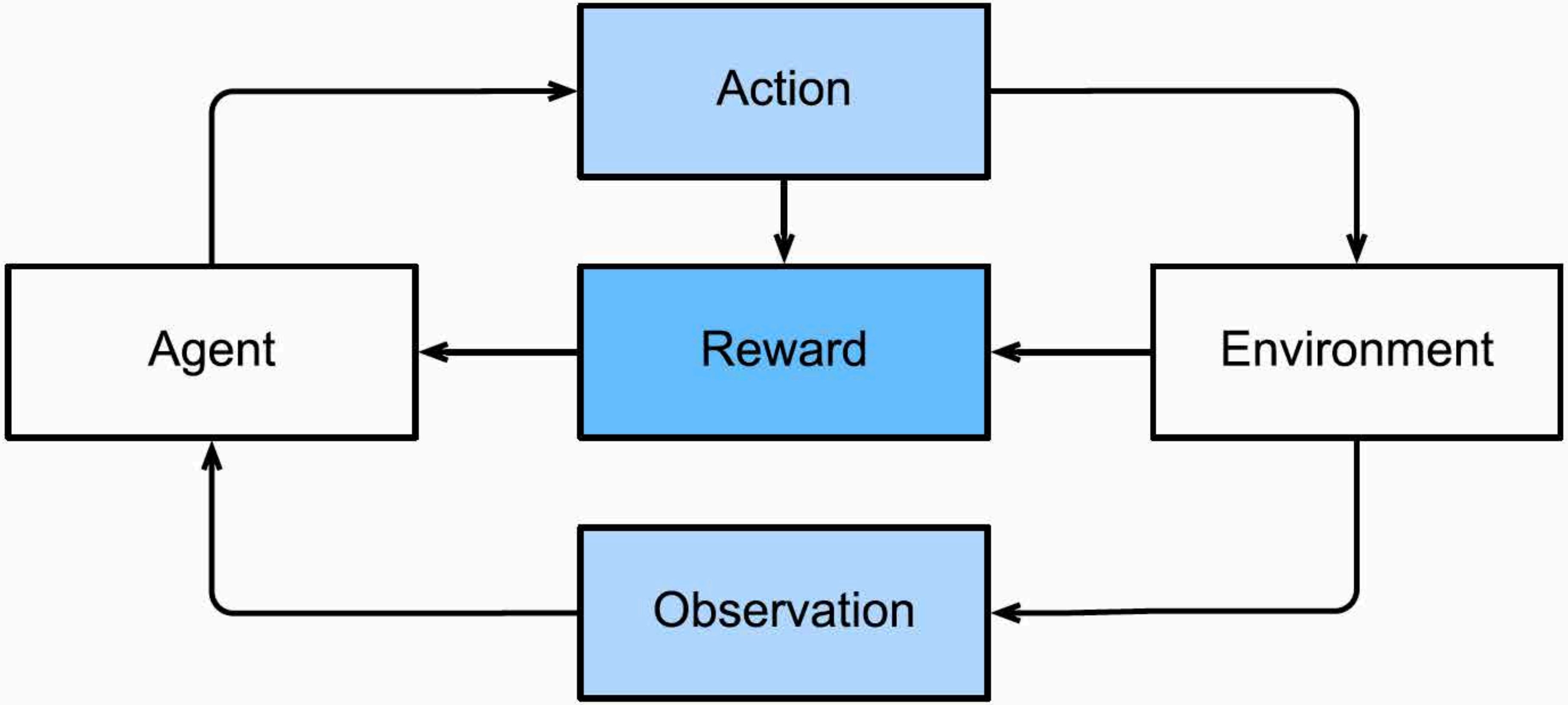


Fig. 3.3.8: The interaction between reinforcement learning and an environment.

Common Language: Convolution Neural Network

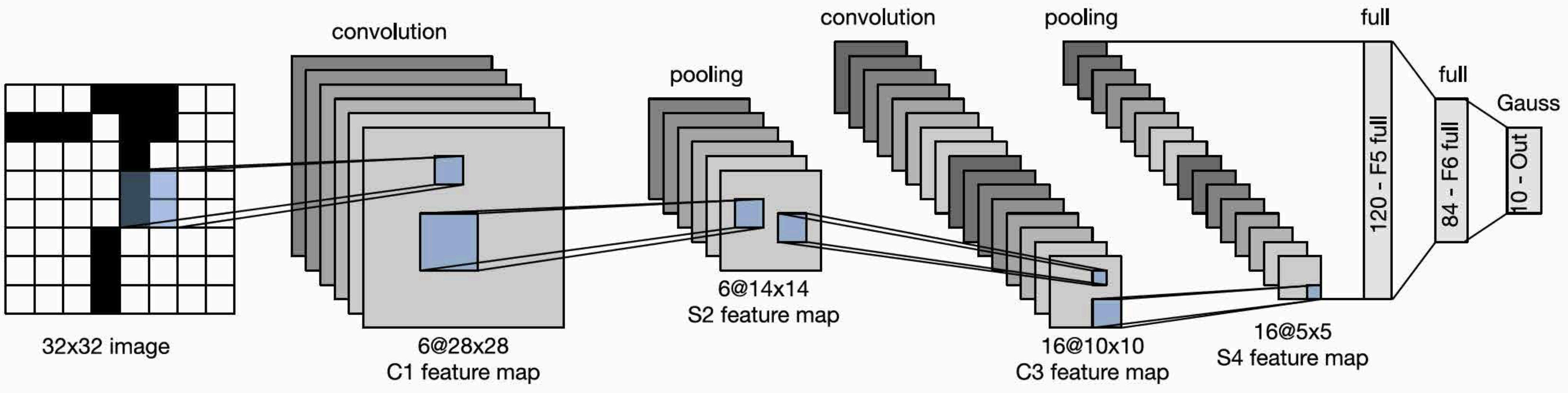


Fig. 8.6.1: Data flow in LeNet 5. The input is a handwritten digit, the output a probabilitiy over 10 possible outcomes.

Common Language: Optimizing Neural Networks

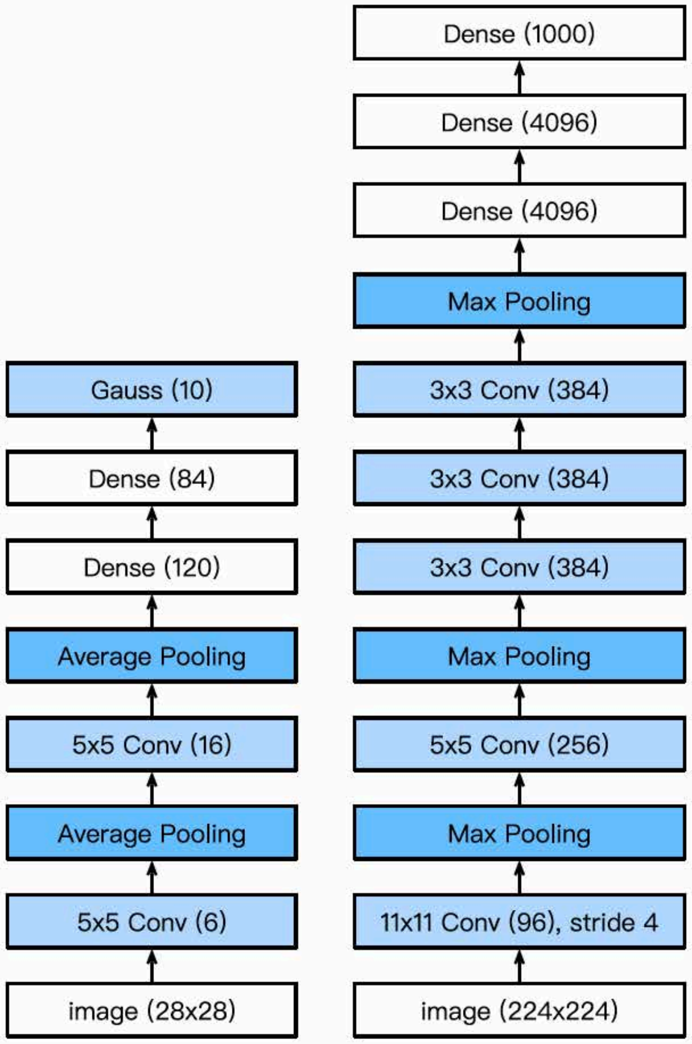


Fig. 9.1.2: LeNet (left) and AlexNet (right)

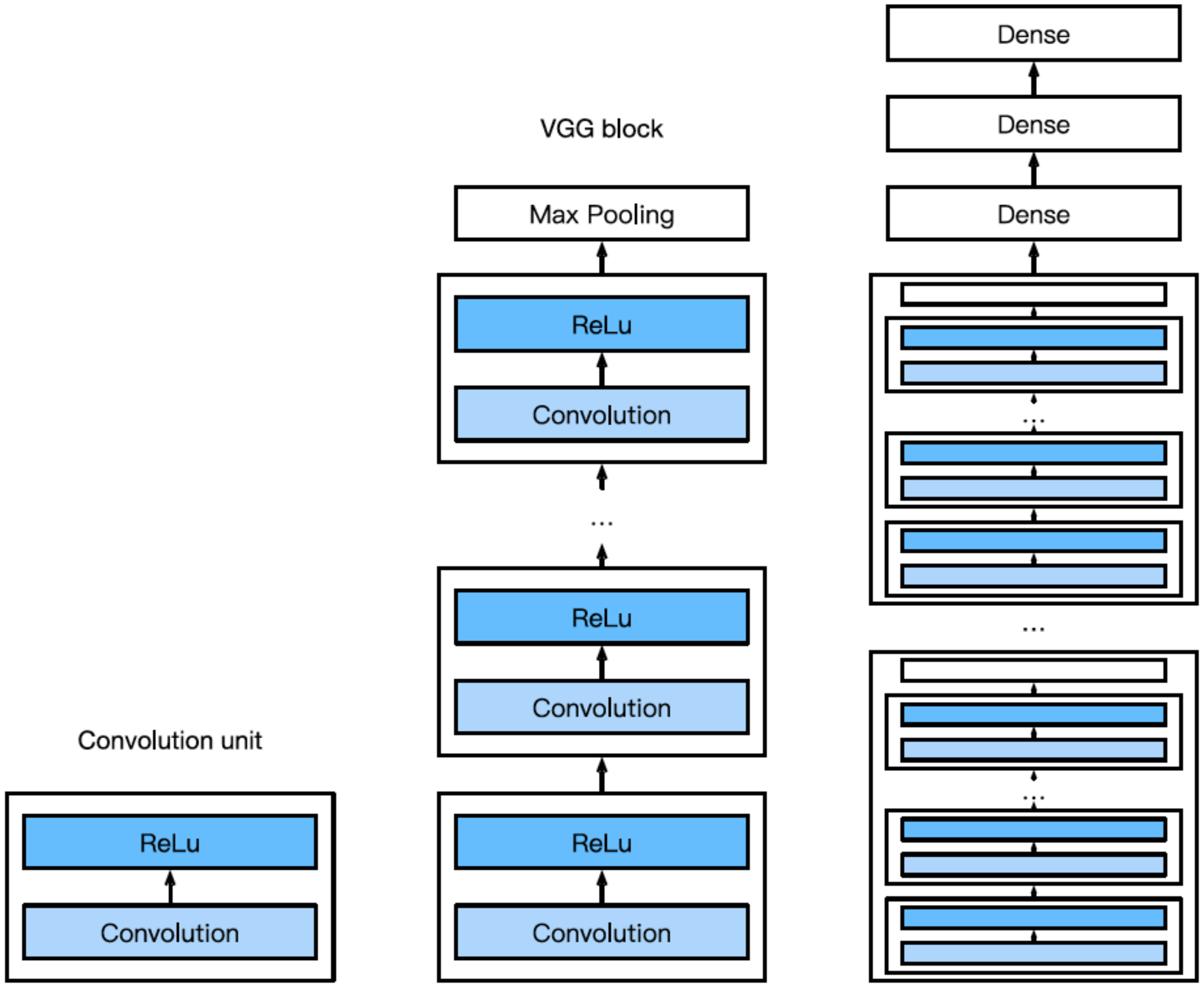


Fig. 9.2.1: Designing a network from building blocks

Common Language: Recurrent Neural Network

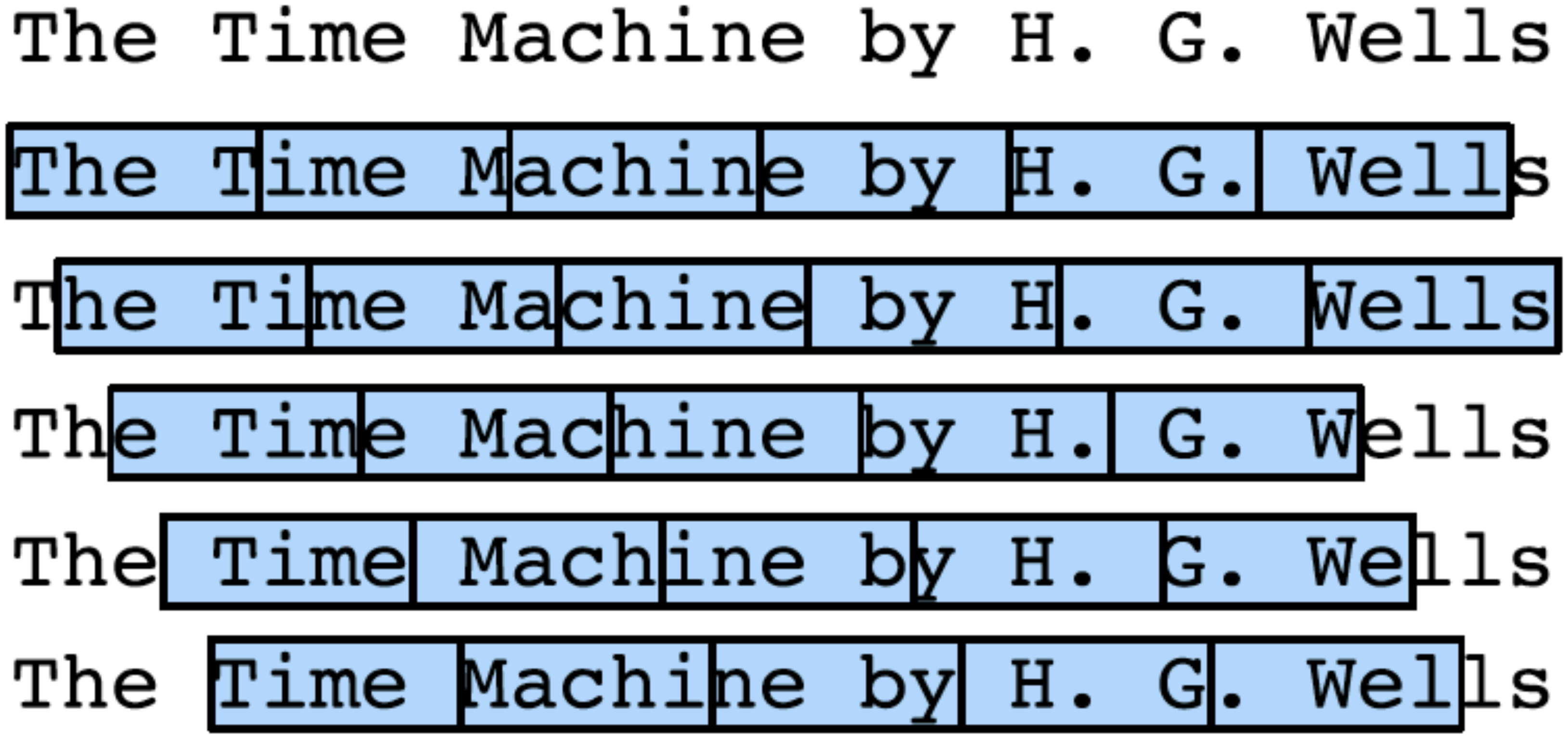


Fig. 10.4.1: Different offsets lead to different subsequences when splitting up text.

Common Language: Recurrent Neural Network

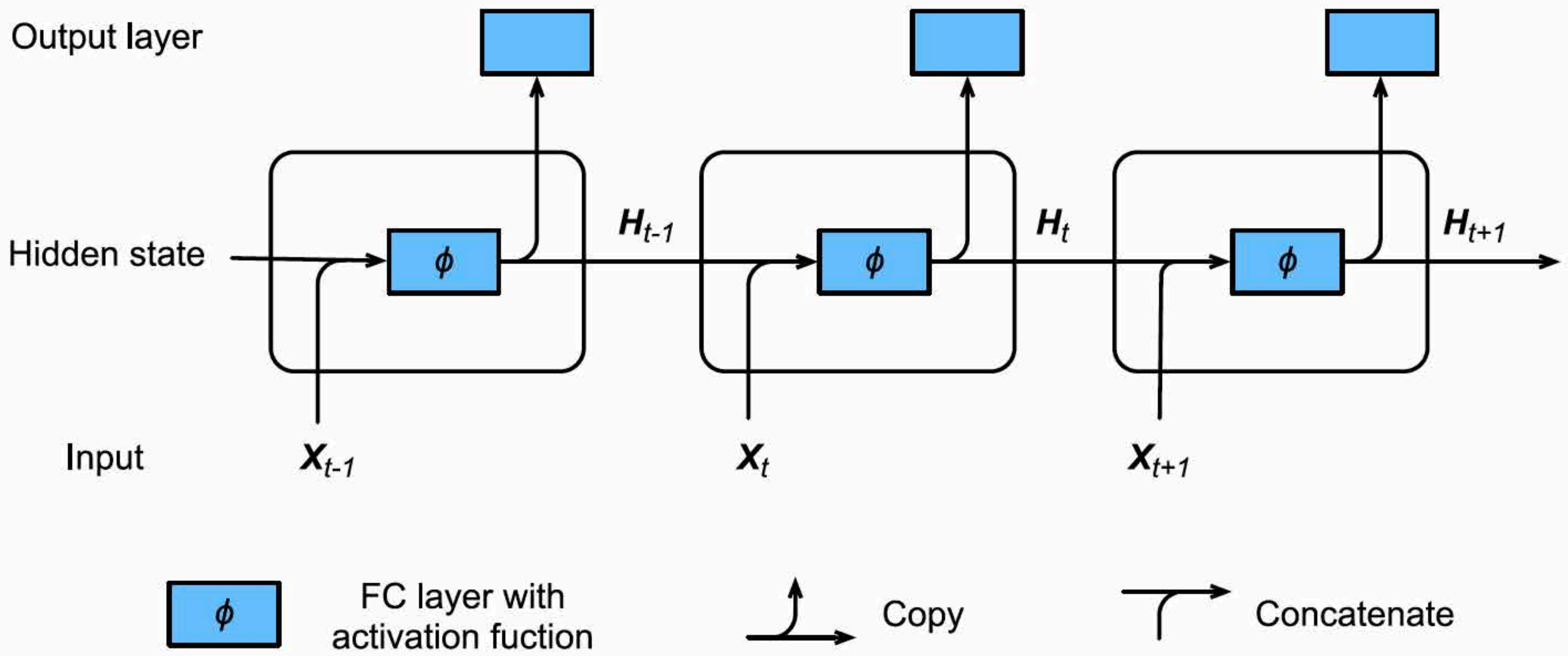


Fig. 10.3.1: An RNN with a hidden state.

Common Language: Recurrent Neural Network

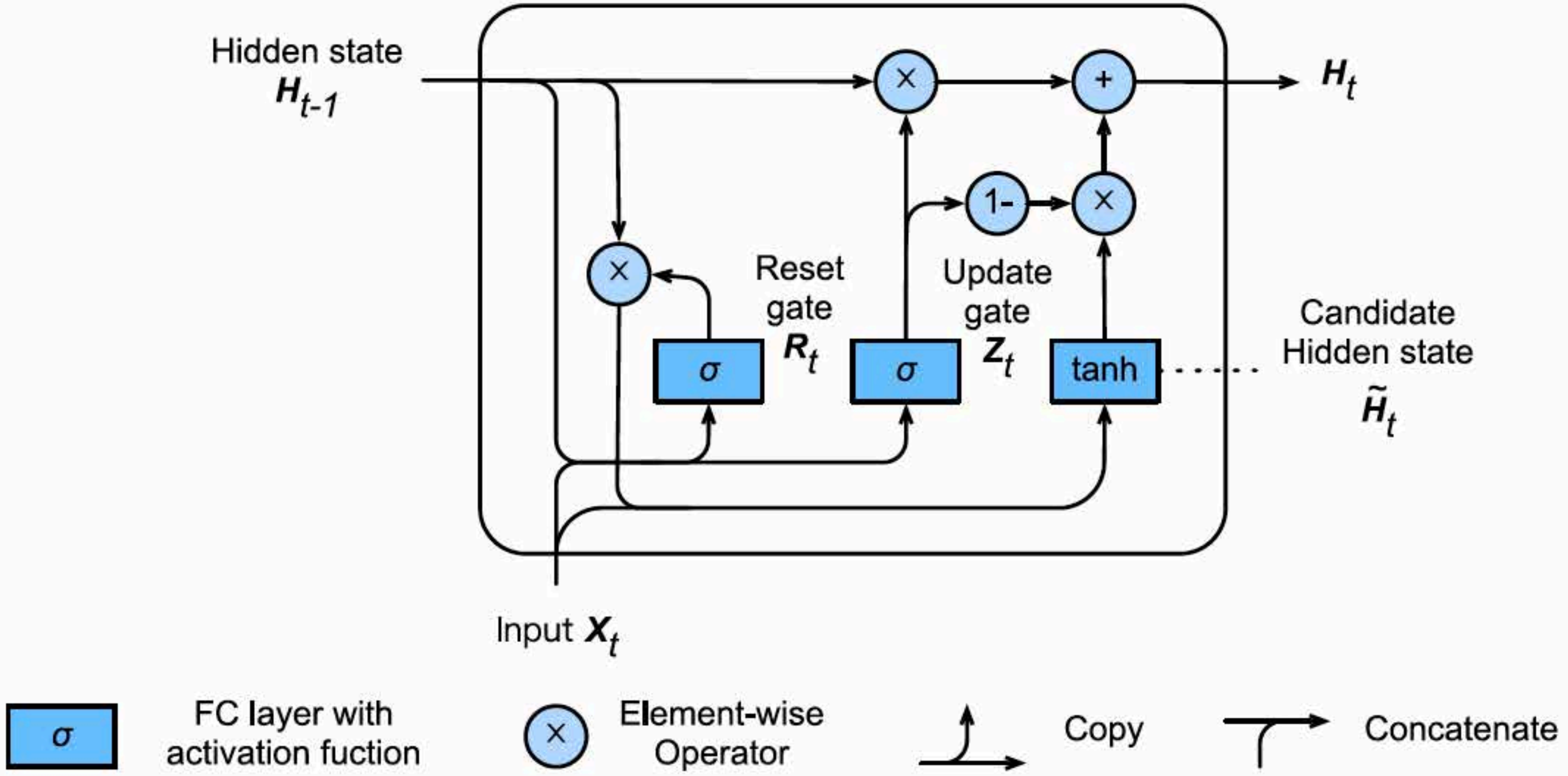


Fig. 10.8.3: Hidden state computation in a GRU. As before, the multiplication is carried out elementwise.

Common Language: Recurrent Neural Network

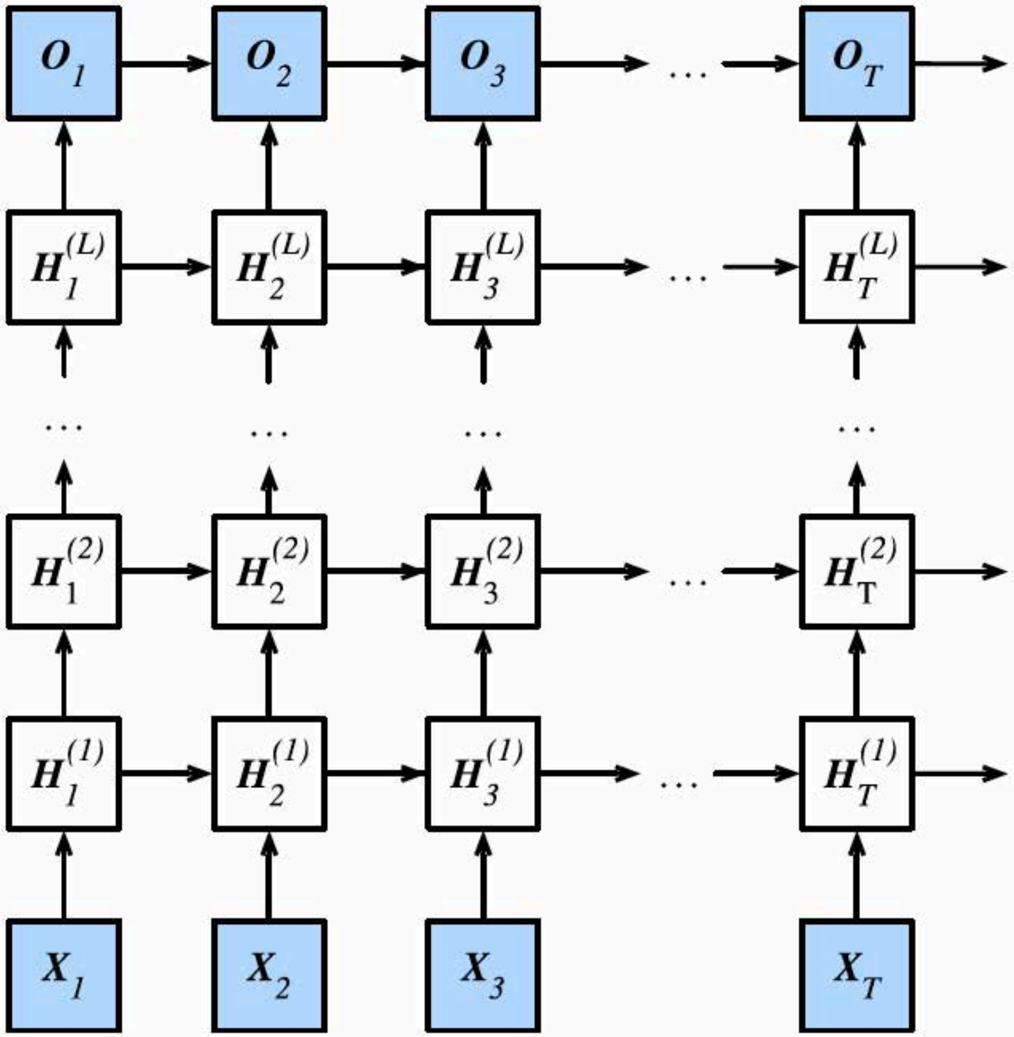


Fig. 10.10.1: Architecture of a deep recurrent neural network.

Common Language: NLP RNNs

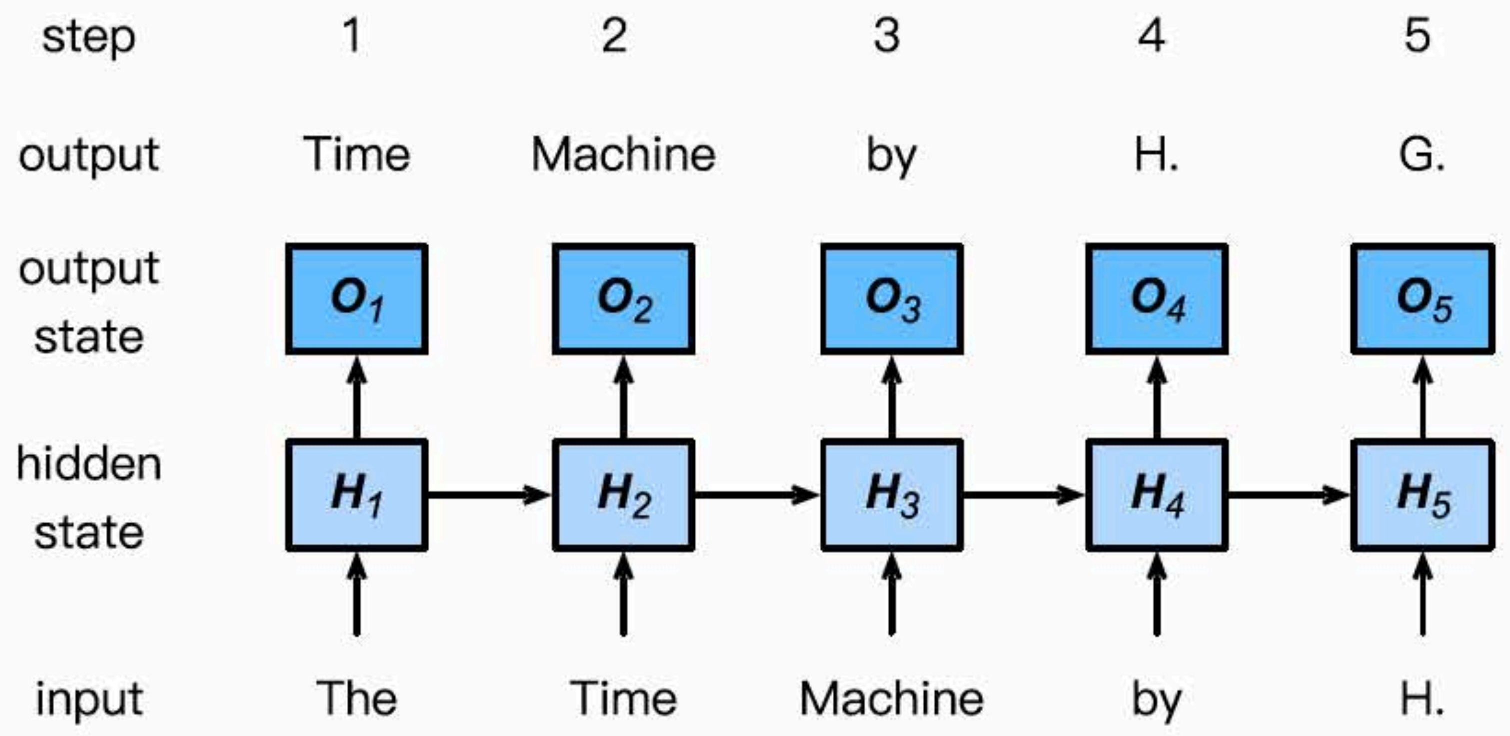


Fig. 10.3.2: Word-level RNN language model. The input and label sequences are `The Time Machine by H.` and `Time Machine by H. G.` respectively.

Common Language: NLP RNNs

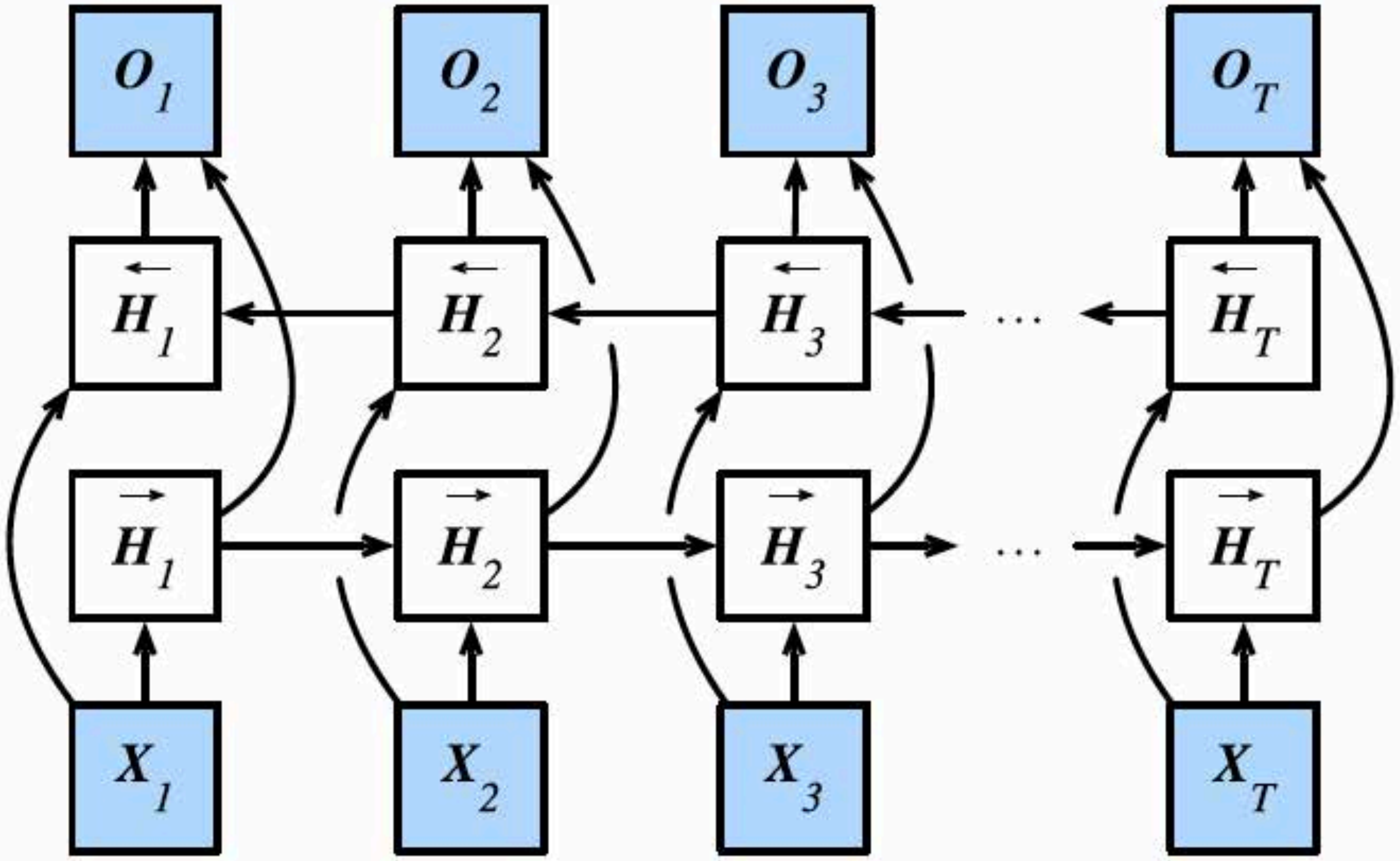


Fig. 10.11.2: Architecture of a bidirectional recurrent neural network.

Common Language: R-CNN

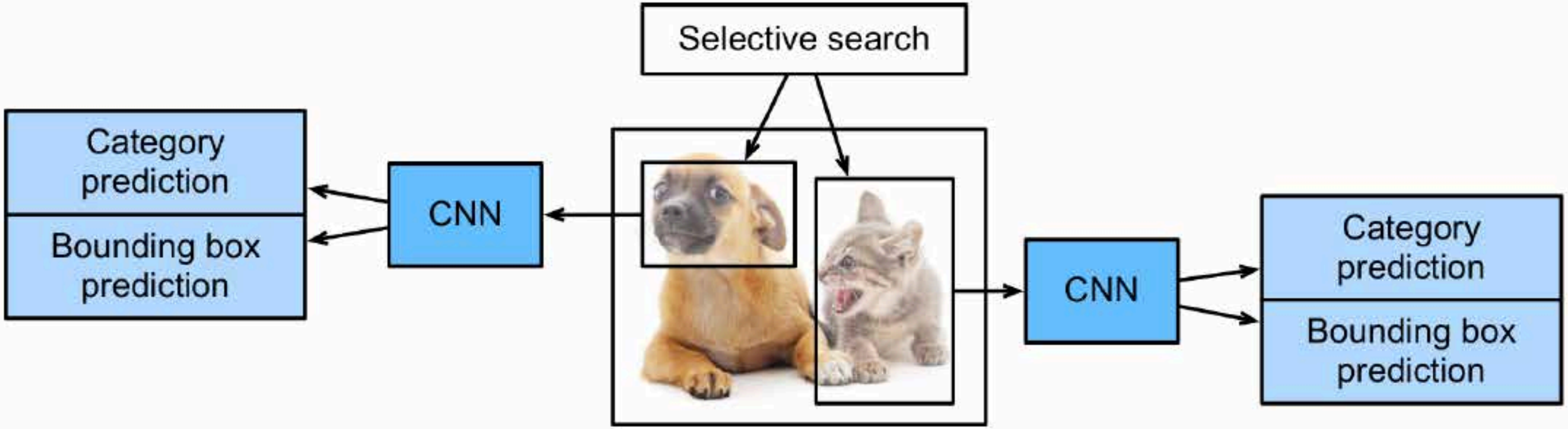


Fig. 14.8.1: R-CNN model.

Common Language: Fast R-CNN

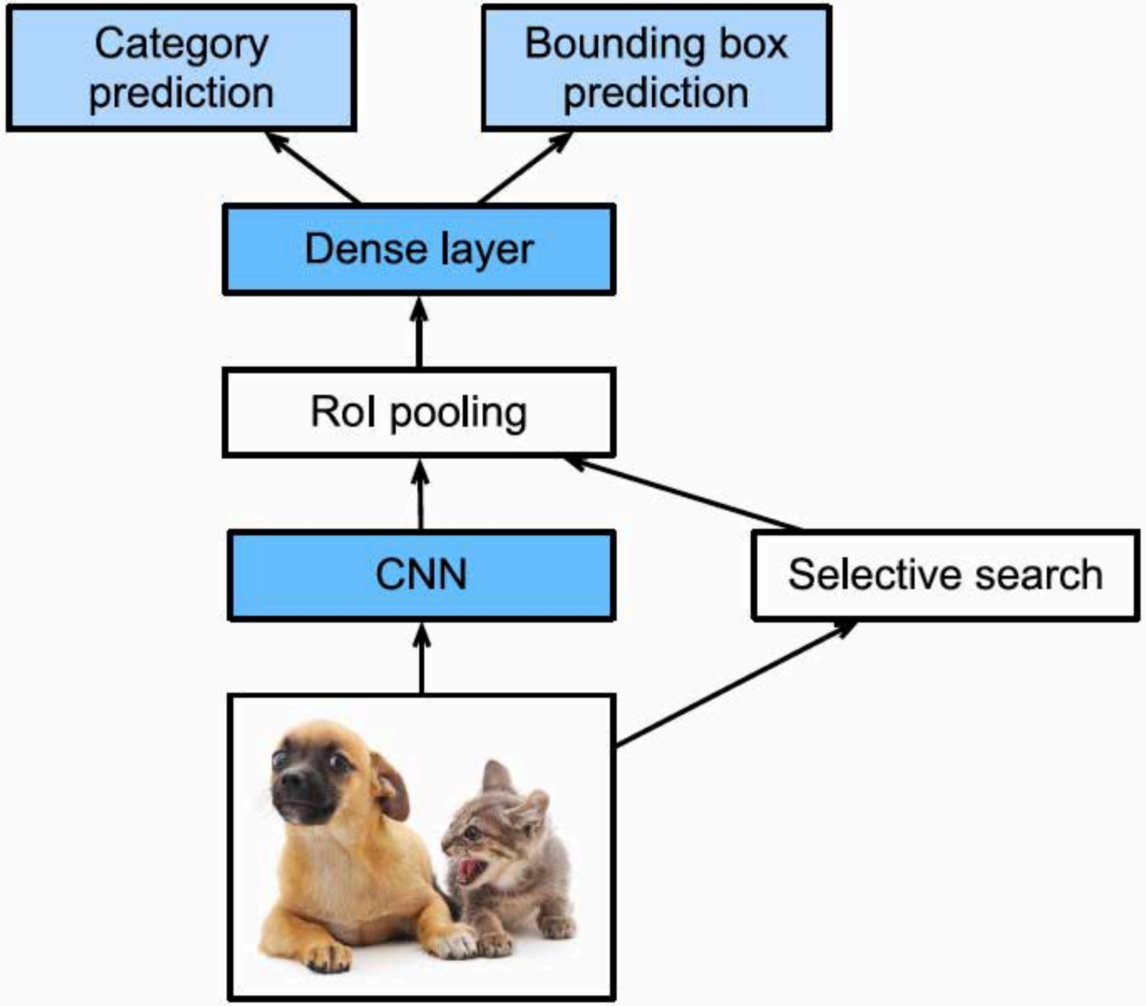


Fig. 14.8.2: Fast R-CNN model.

Common Language: Faster R-CNN

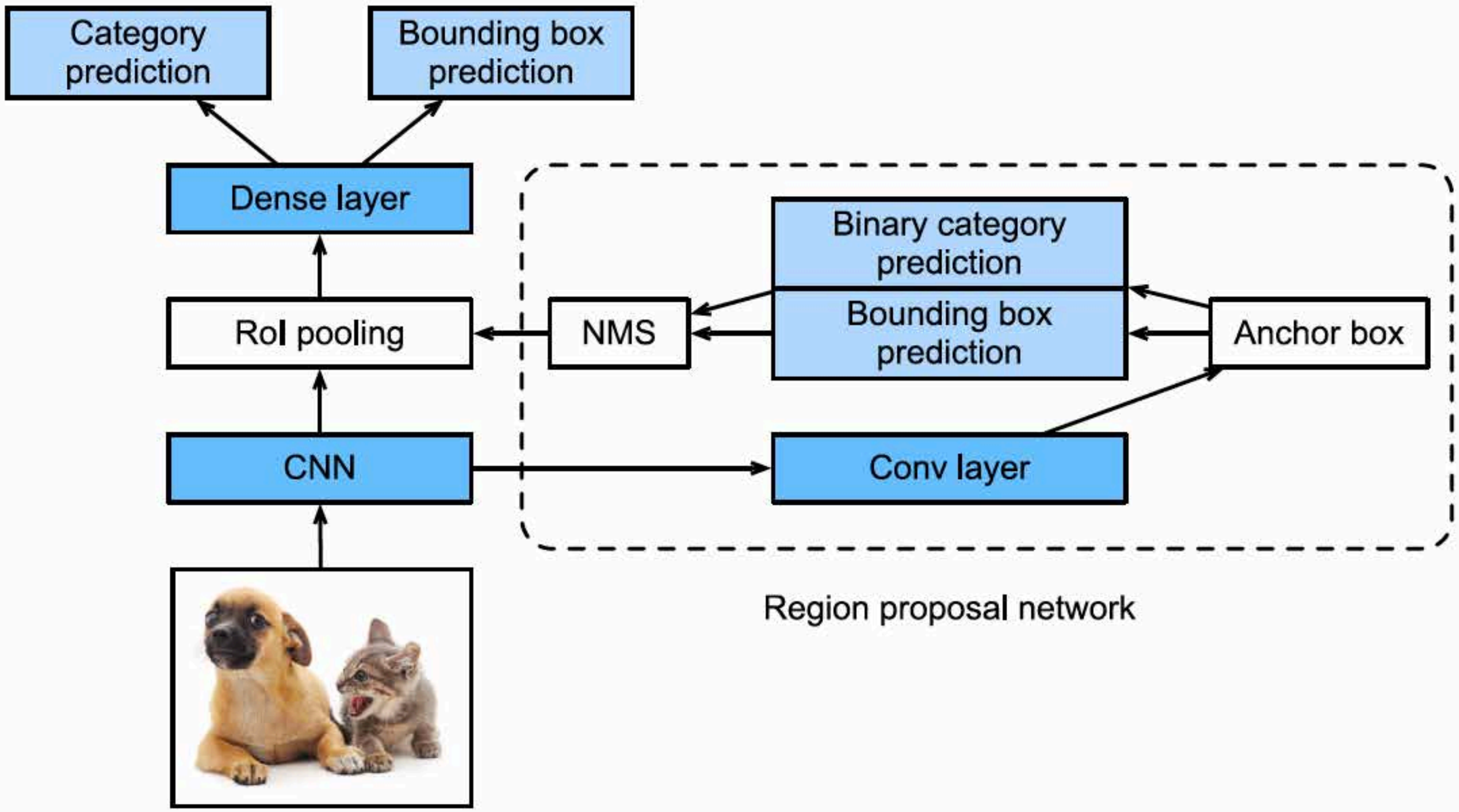


Fig. 14.8.4: Faster R-CNN model.

Common Language: Mask R-CNN

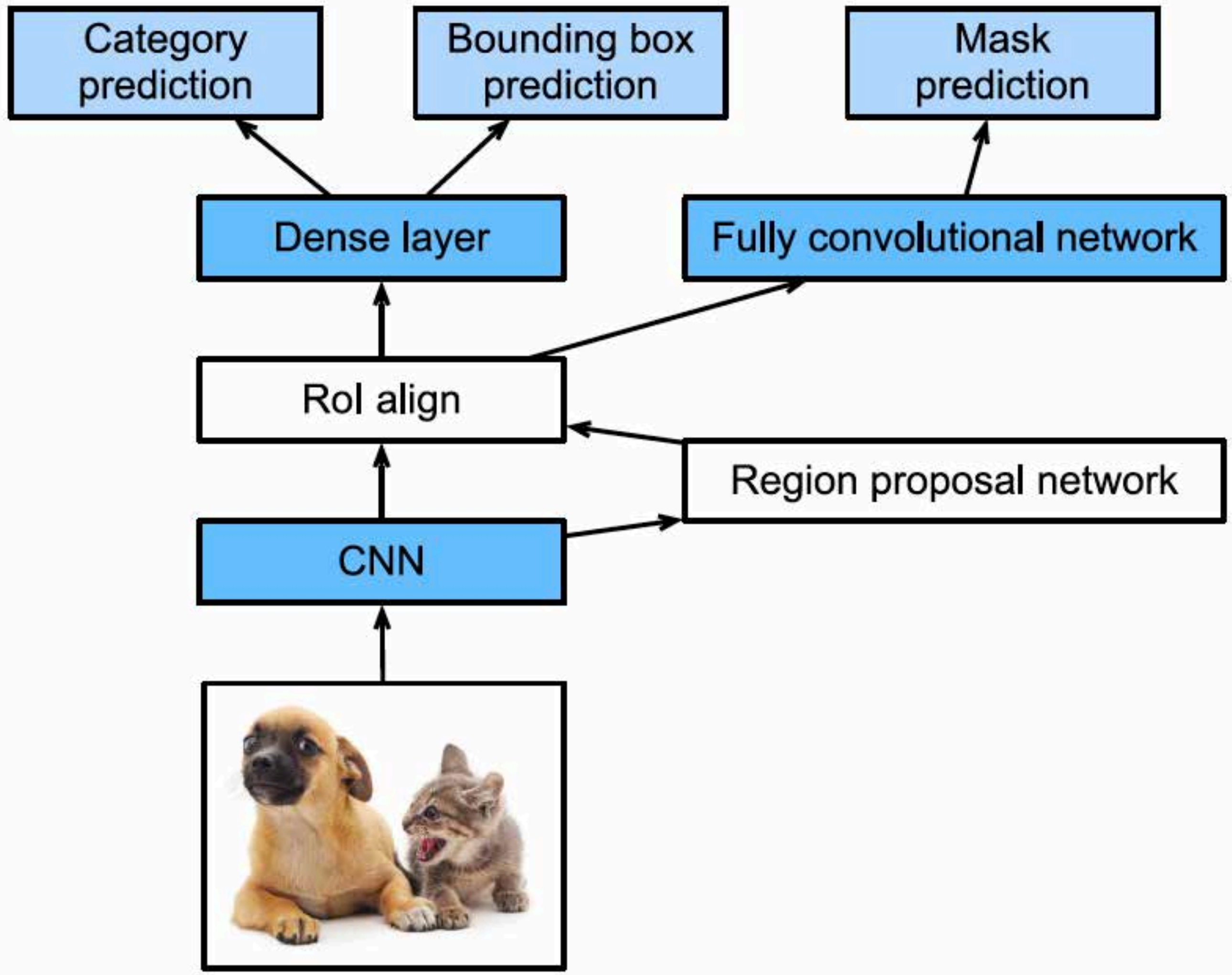
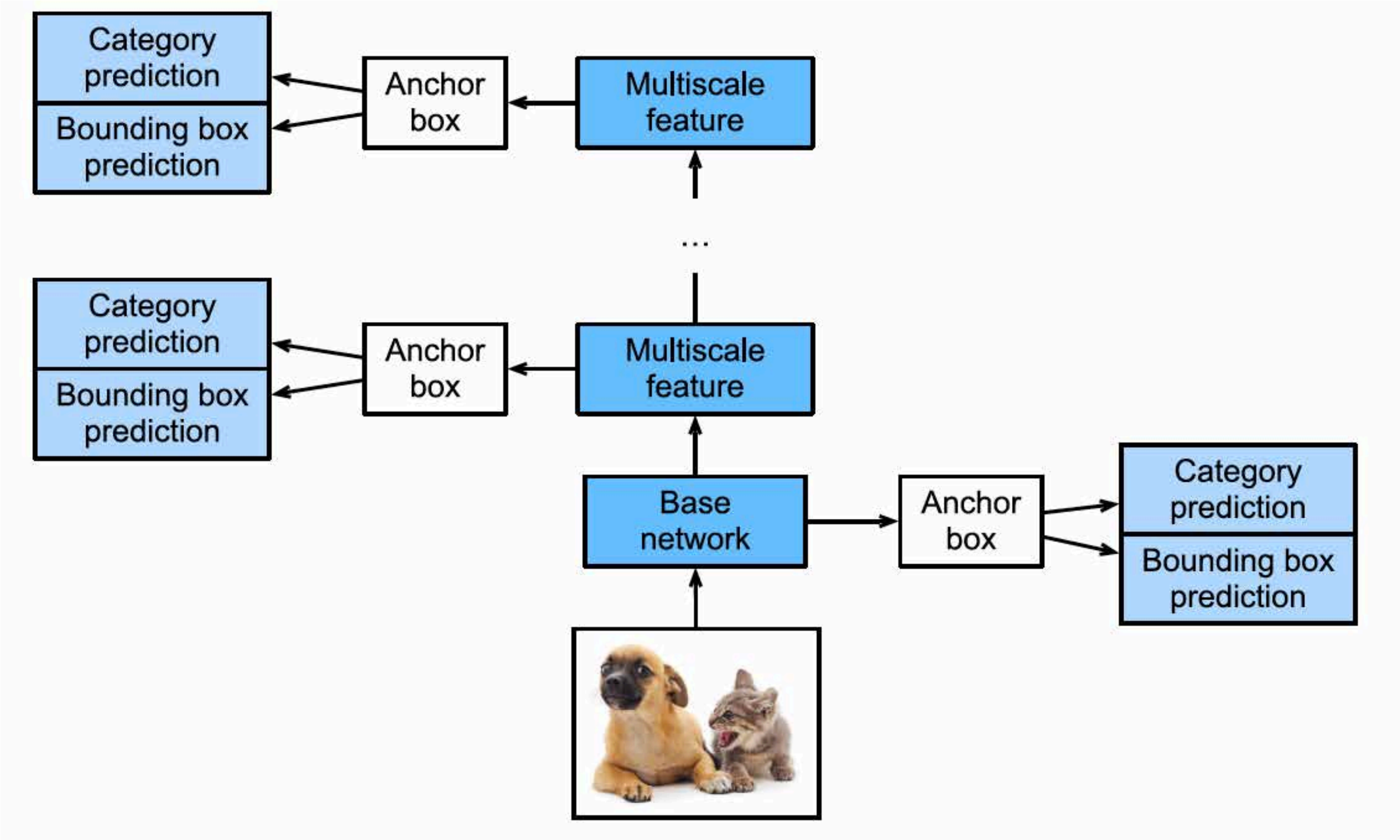
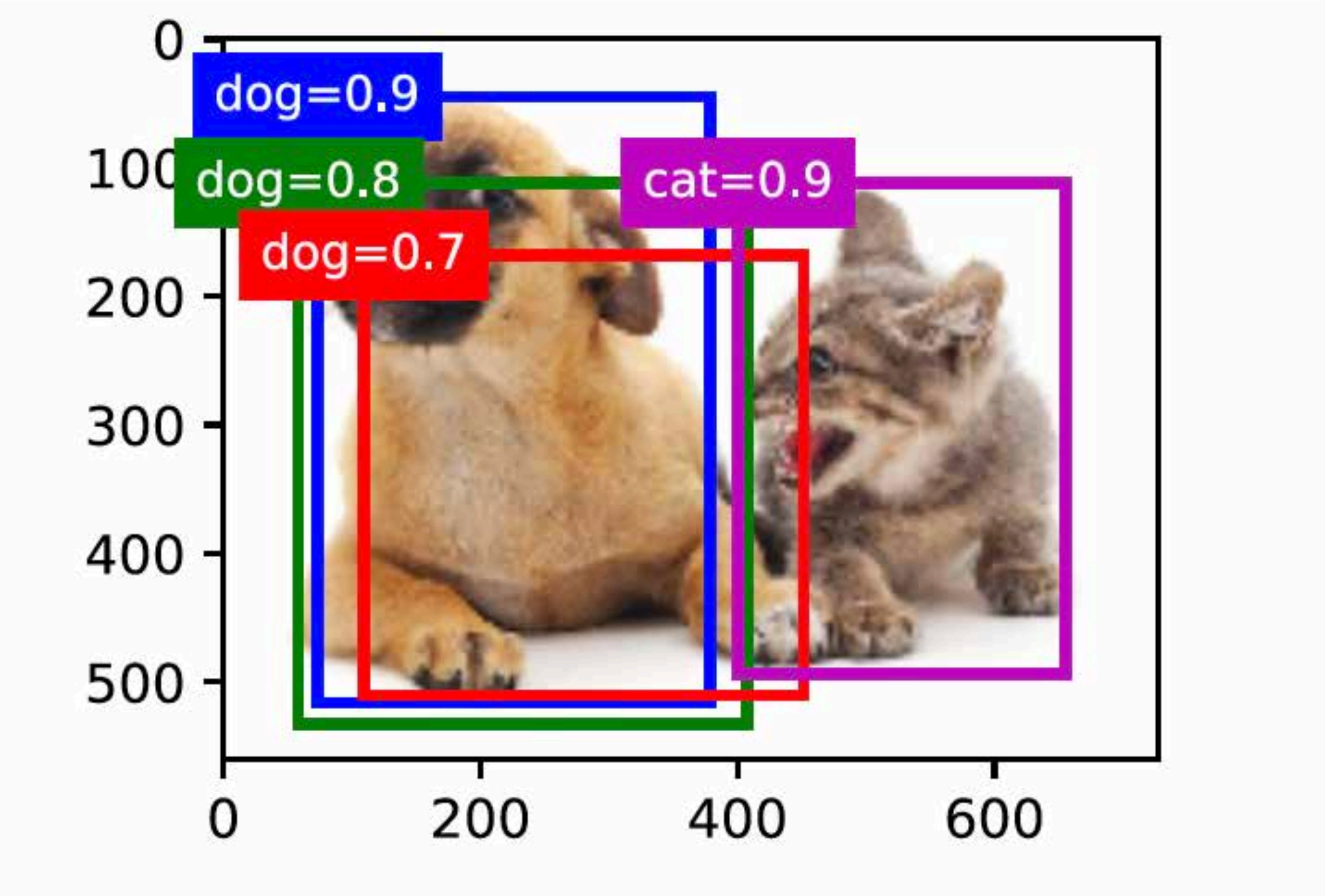


Fig. 14.8.5: Mask R-CNN model.

Common Language: Segment Analysis



Common Language: Segment Analysis



Common Language: Transfer Learning

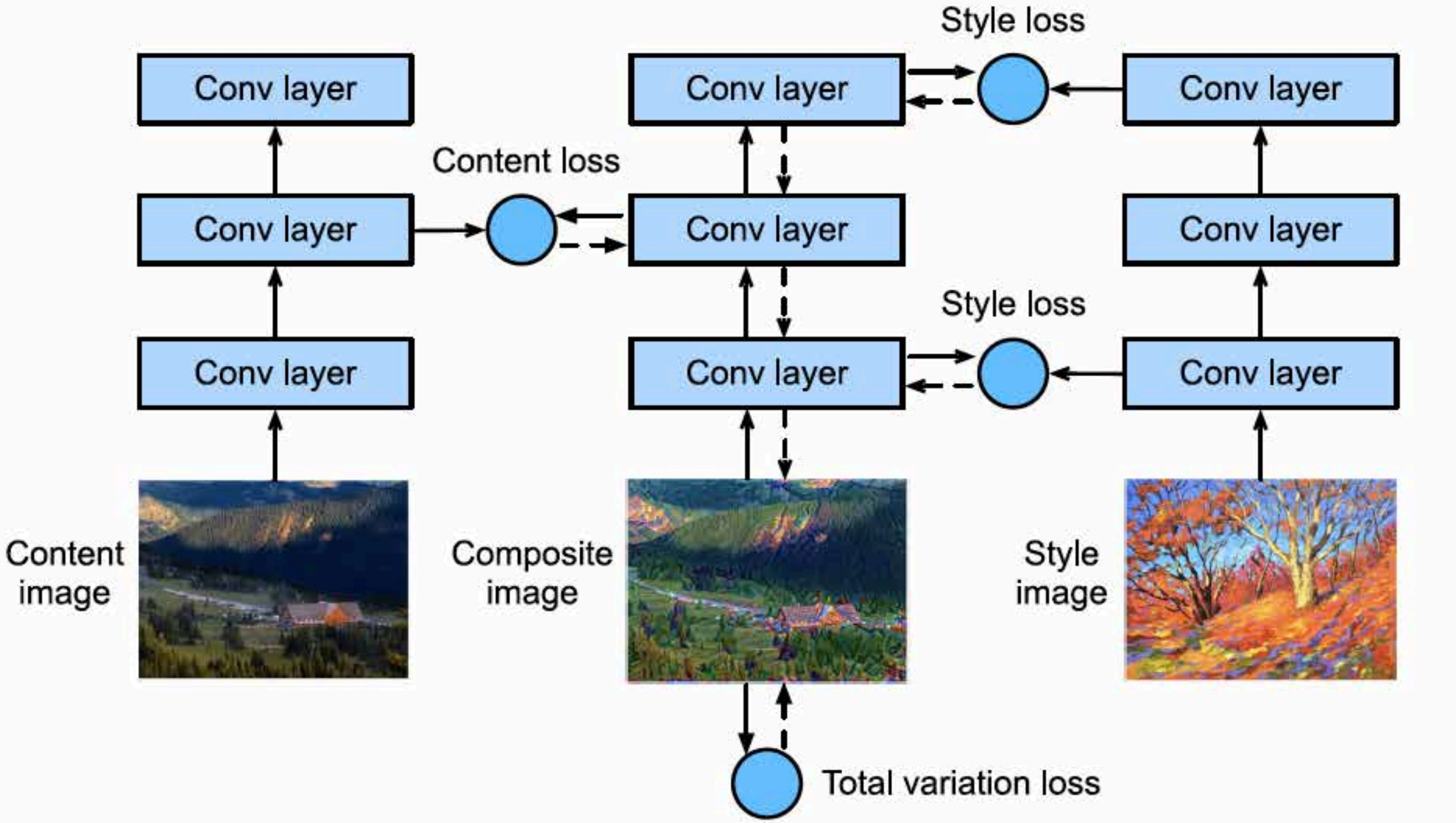


Fig. 14.11.2: CNN-based style transfer process. Solid lines show the direction of forward propagation and dotted lines show backward propagation.

Common Language: Data Science Workflow

01

Identify the problem

What is the challenge you would like to solve? What is the hypothesis and critical goals for success?

02

Acquire the data

Identify the right data sets and tools to work with. Read documentation and review the data.

03

Refine the data

Clean the data and add calculations to better explain and understand your data.

04

Build data models

Whether visualizations, or data science models, explore the insights and trends that you can reveal from your data.

05

Communicate your results

Create a dashboard, a report, presentation, or machine learning pipeline to share the outcomes with both your internal and external stakeholders

Solving Common Issues: Data Wrangling

sklearn.preprocessing: Preprocessing and Normalization

The `sklearn.preprocessing` module includes scaling, centering, normalization, binarization and imputation methods.

User guide: See the Preprocessing data section for further details.

`preprocessing.Binarizer` ([threshold, copy])	Binarize data (set feature values to 0 or 1) according to a threshold
`preprocessing.FunctionTransformer` ([func, …])	Constructs a transformer from an arbitrary callable.
`preprocessing.KBinsDiscretizer` ([n_bins, …])	Bin continuous data into intervals.
`preprocessing.KernelCenterer` ()	Center a kernel matrix
`preprocessing.LabelBinarizer` ([neg_label, …])	Binarize labels in a one-vs-all fashion
`preprocessing.LabelEncoder`	Encode labels with value between 0 and n_classes-1.
`preprocessing.MultiLabelBinarizer` ([classes, …])	Transform between iterable of iterables and a multilabel format
`preprocessing.MaxAbsScaler` ([copy])	Scale each feature by its maximum absolute value.
`preprocessing.MinMaxScaler` ([feature_range, copy])	Transforms features by scaling each feature to a given range.
`preprocessing.Normalizer` ([norm, copy])	Normalize samples individually to unit norm.
`preprocessing.OneHotEncoder` ([n_values, …])	Encode categorical integer features as a one-hot numeric array.
`preprocessing.OrdinalEncoder` ([categories, dtype])	Encode categorical features as an integer array.
`preprocessing.PolynomialFeatures` ([degree, …])	Generate polynomial and interaction features.
`preprocessing.PowerTransformer` ([method, …])	Apply a power transform featurewise to make data more Gaussian-like.
`preprocessing.QuantileTransformer` ([…])	Transform features using quantiles information.
`preprocessing.RobustScaler` ([with_centering, …])	Scale features using statistics that are robust to outliers.
`preprocessing.StandardScaler` ([copy, …])	Standardize features by removing the mean and scaling to unit variance
`preprocessing.add_dummy_feature` (X[, value])	Augment dataset with an additional dummy feature.
`preprocessing.binarize` (X[, threshold, copy])	Boolean thresholding of array-like or scipy.sparse matrix
`preprocessing.label_binarize` (y, classes[, …])	Binarize labels in a one-vs-all fashion
`preprocessing.maxabs_scale` (X[, axis, copy])	Scale each feature to the [-1, 1] range without breaking the sparsity.
`preprocessing.minmax_scale` (X[, …])	Transforms features by scaling each feature to a given range.
`preprocessing.normalize` (X[, norm, axis, …])	Scale input vectors individually to unit norm (vector length).
`preprocessing.quantile_transform` (X[, axis, …])	Transform features using quantiles information.
`preprocessing.robust_scale` (X[, axis, …])	Standardize a dataset along any axis
`preprocessing.scale` (X[, axis, with_mean, …])	Standardize a dataset along any axis
`preprocessing.power_transform` (X[, method, …])	Power transforms are a family of parametric, monotonic transformations that are applied to make data more Gaussian-like.

sklearn.pipeline: Pipeline

The `sklearn.pipeline` module implements utilities to build a composite estimator, as a chain of transforms and estimators.

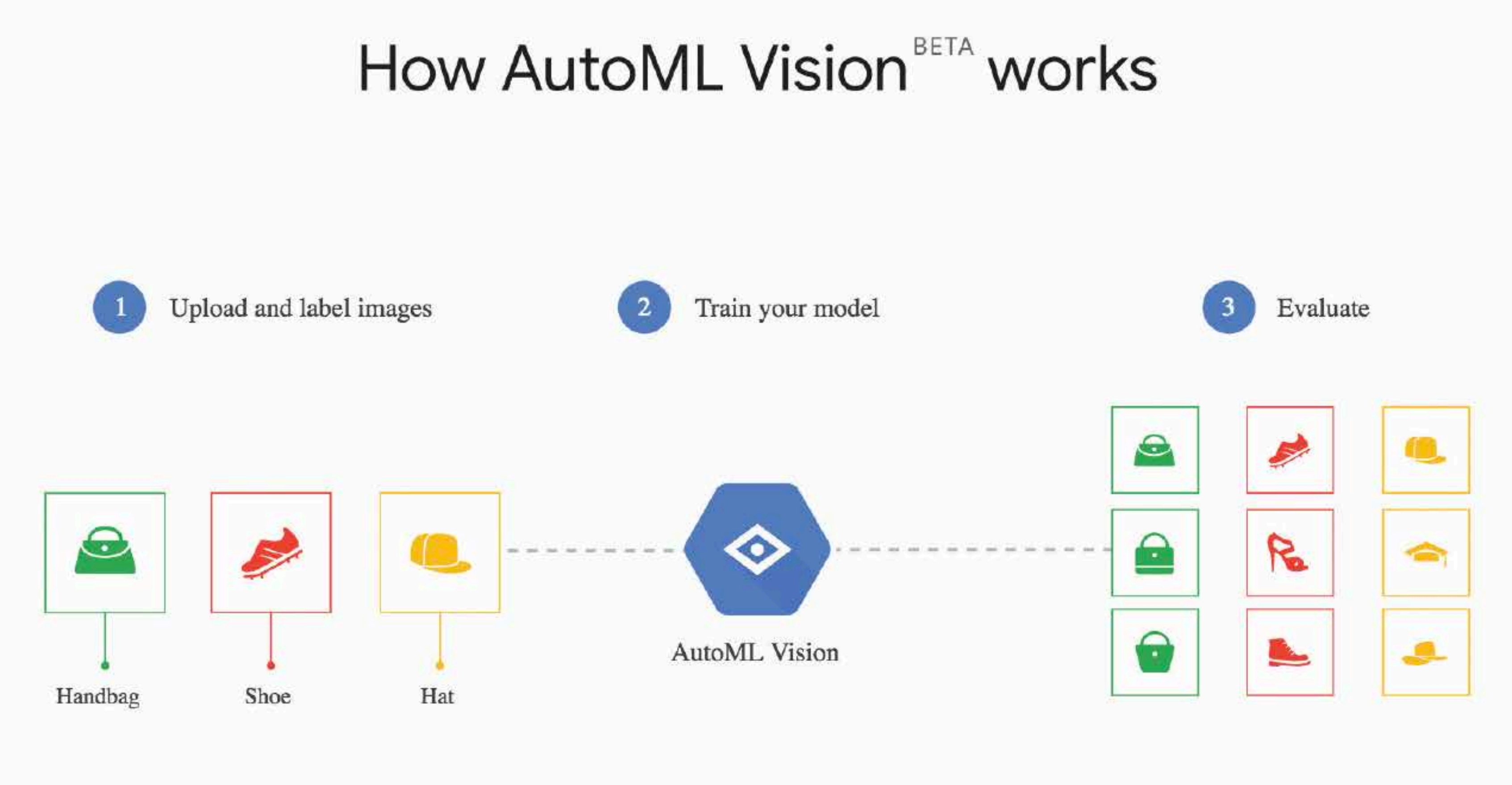
`pipeline.FeatureUnion` (transformer_list[, …])	Concatenates results of multiple transformer objects.
`pipeline.Pipeline` (steps[, memory, verbose])	Pipeline of transforms with a final estimator.
`pipeline.make_pipeline` (*steps, **kwargs)	Construct a Pipeline from the given estimators.
`pipeline.make_union` (*transformers, **kwargs)	Construct a FeatureUnion from the given transformers.

pandas $y_{it} = \beta' x_{it} + \mu_i + \epsilon_{it}$

scikit learn

Featuretools

Solving Common Issues: Data Pipelines



Google Cloud's AutoML Vision allows users to train high-quality custom vision models.

Solving Common Issues: Data Platforms

Figure 1. Magic Quadrant for Data Science and Machine Learning Platforms

Source: Gartner (January 2019)

Common Language: Data Science Workflow

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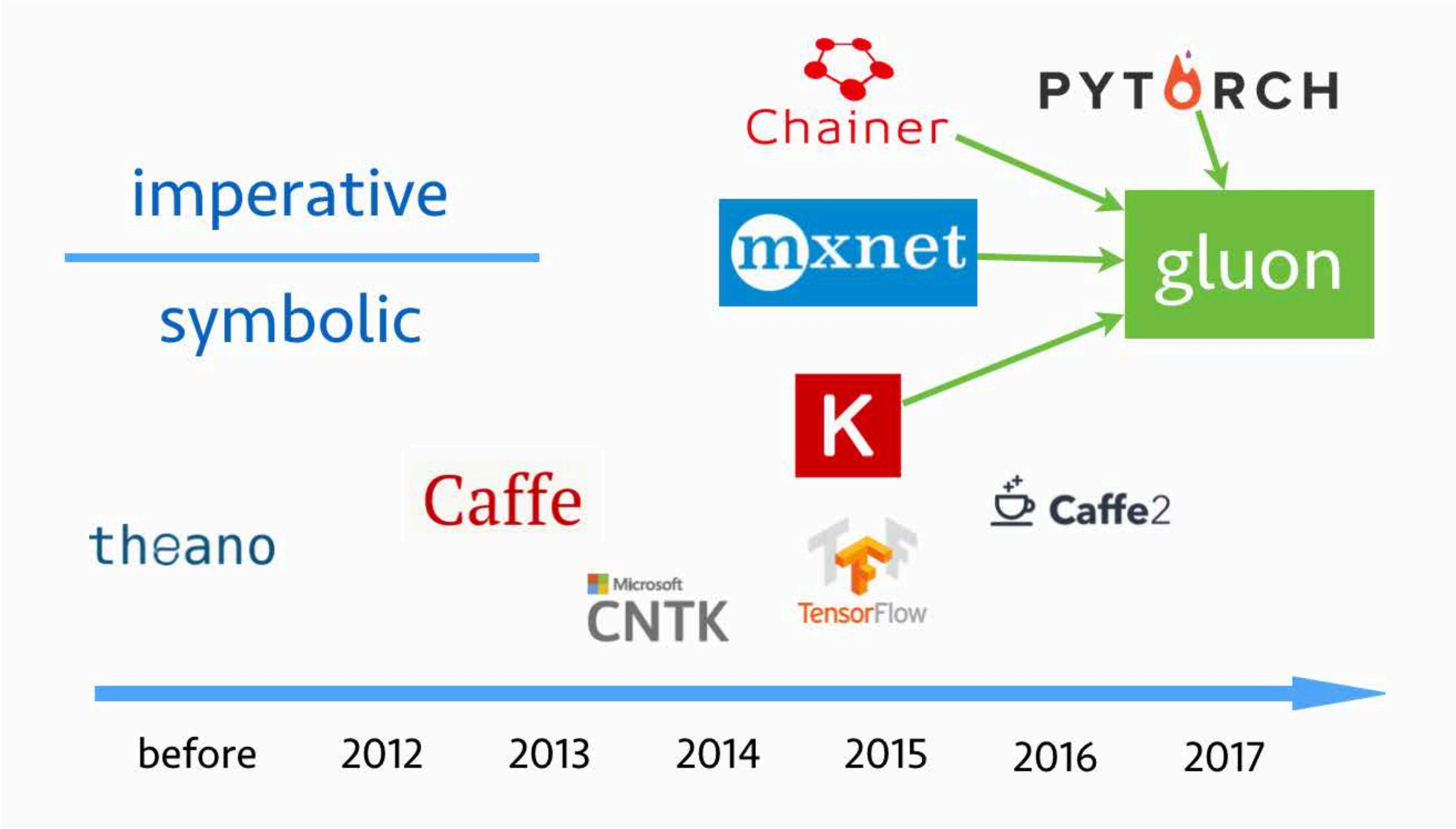
Solving Common Issues: Data Libraries



Common Language: Data Science Workflow

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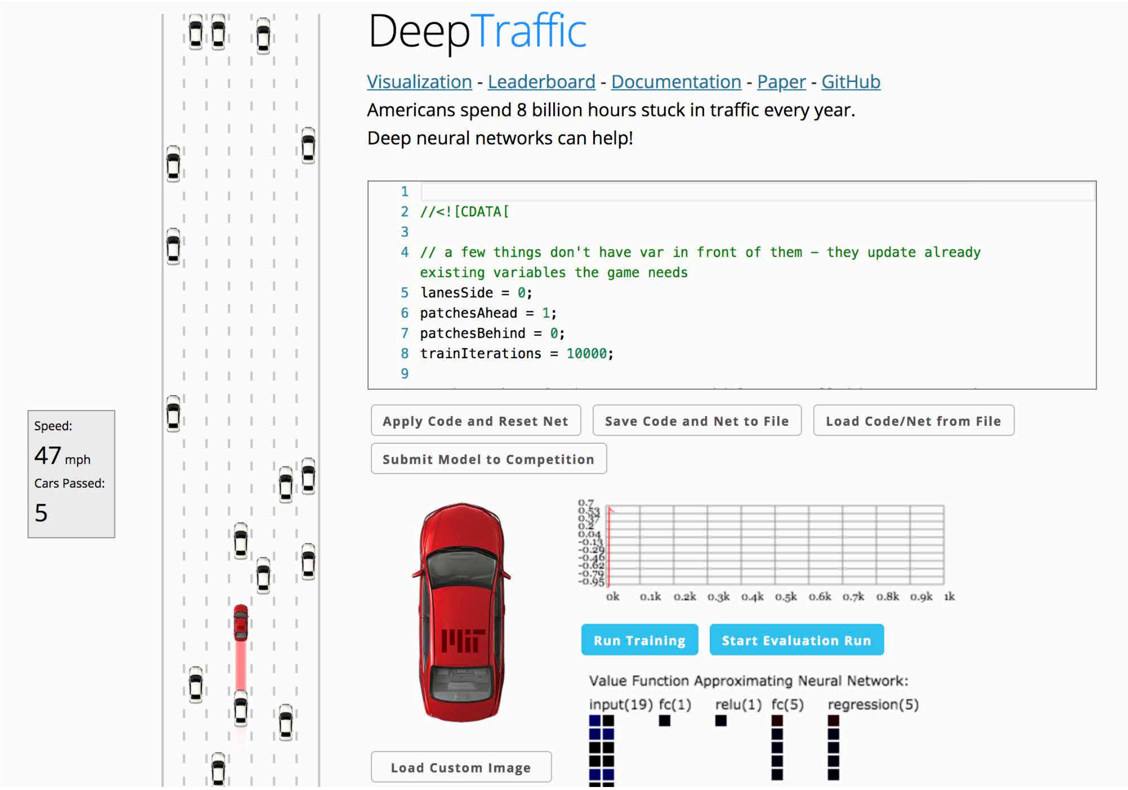
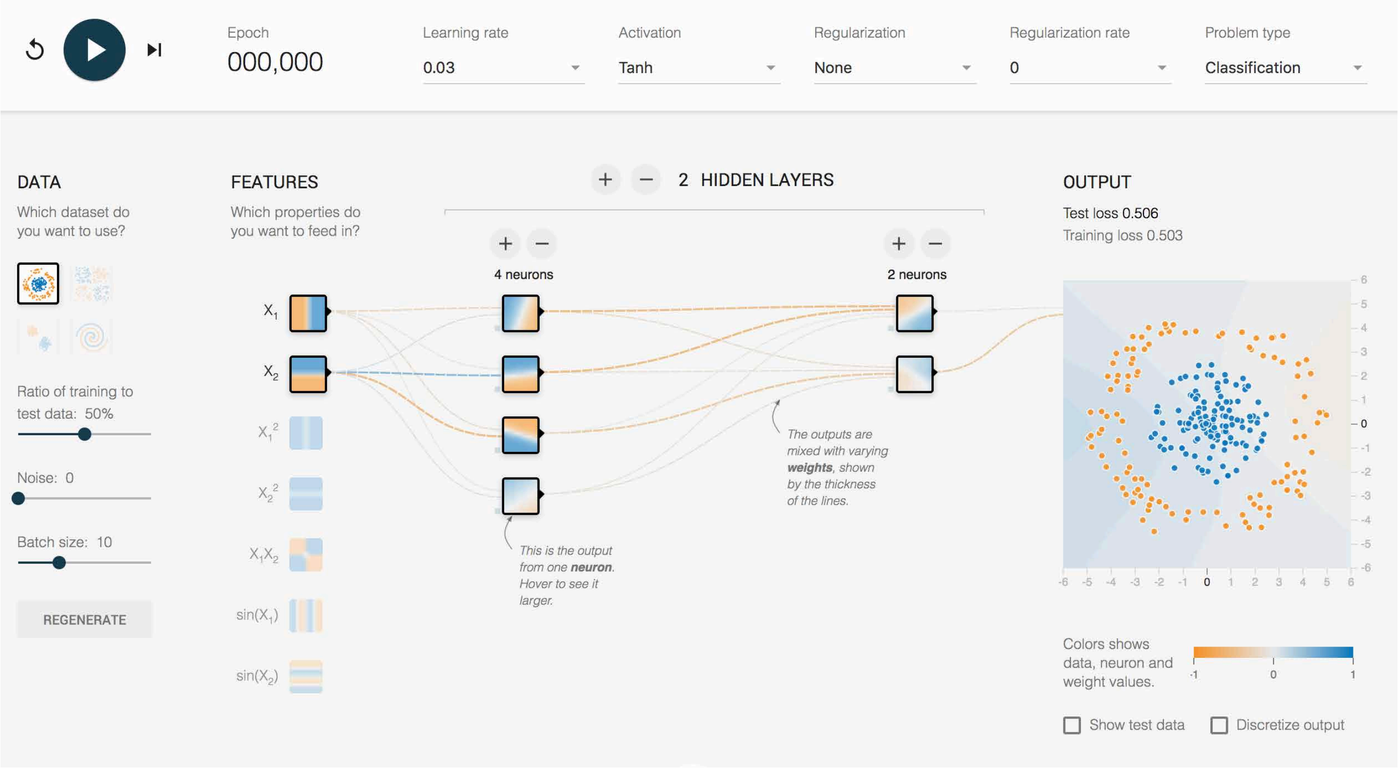
AI Demo: DeepTraffic at MIT



bit.ly/mitselfdriving

Deep Traffic

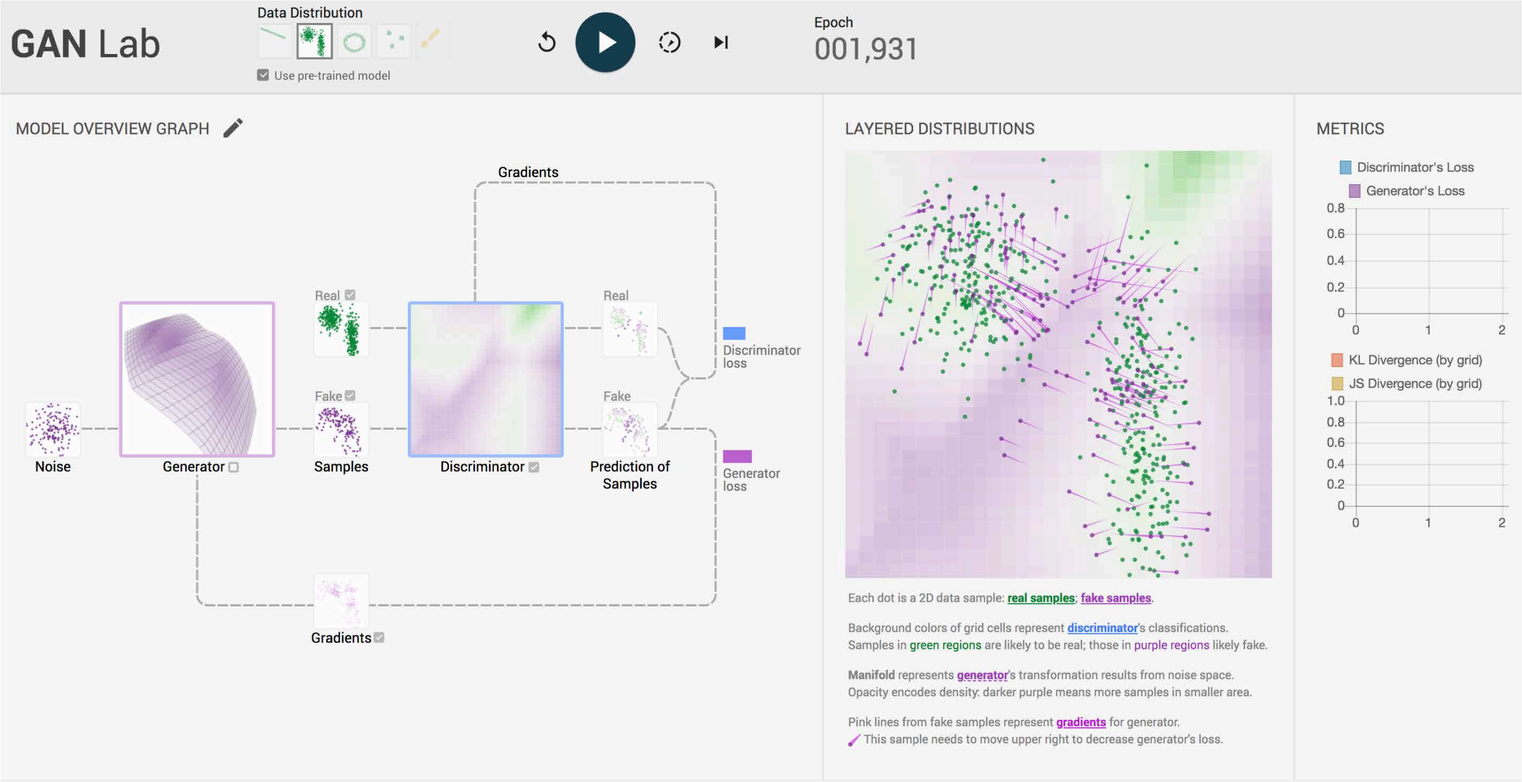
AI Demo: TensorFlow Playground at Google



bit.ly/tensorplay

TF Playground

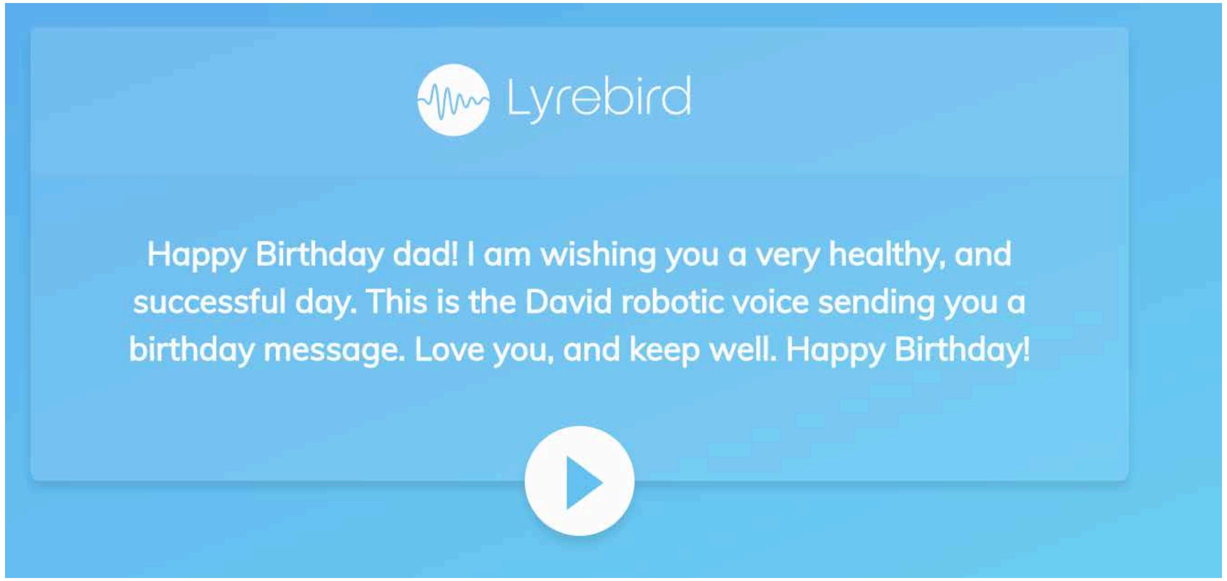
AI Demo: GANs Lab at Georgia Tech & Google



bit.ly/ganlabdemo

GANs Lab

AI Demo: David's Voice on Lyrebird



bit.ly/davidrobotvoice

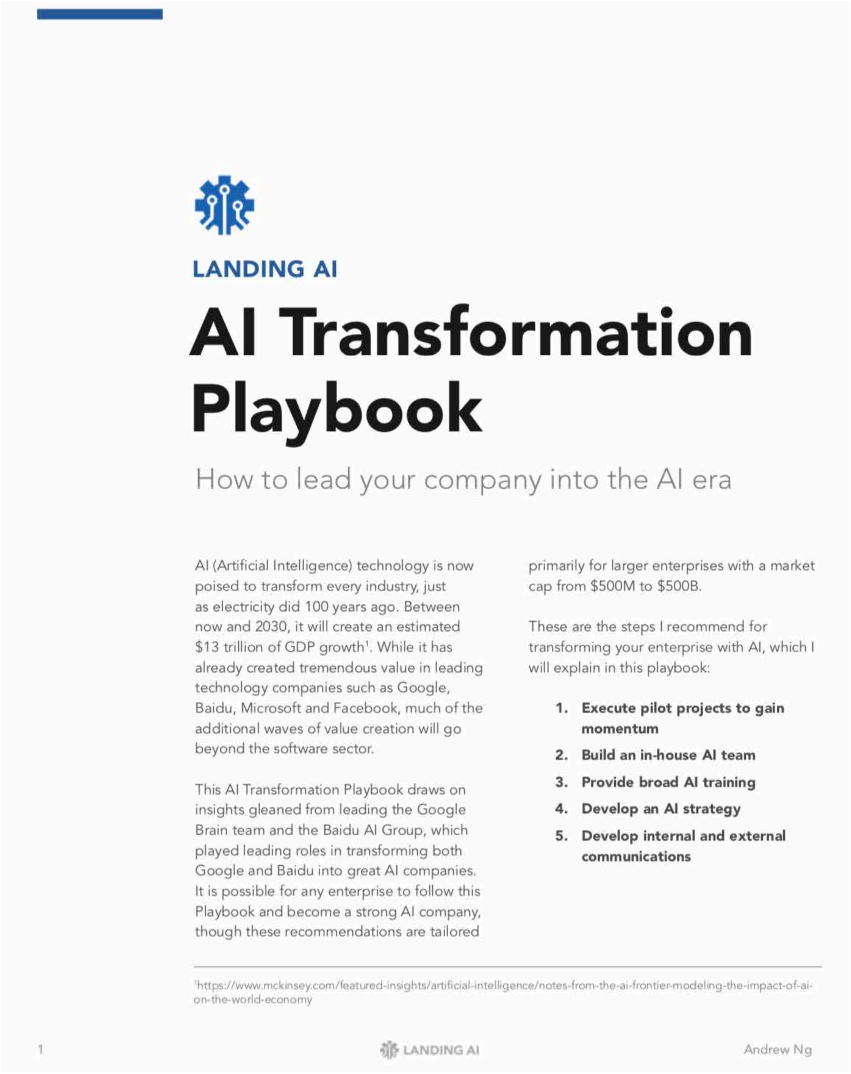
David-Robot

AI Demo: Detect Auto-Text at MIT/IBM/Harvard

bit.ly/autotextdetect

Auto Text

AI Ethics



LANDING AI

AI Transformation Playbook

How to lead your company into the AI era

AI (Artificial Intelligence) technology is now poised to transform every industry, just as electricity did 100 years ago. Between now and 2030, it will create an estimated $13 trillion of GDP growth[1]. While it has already created tremendous value in leading technology companies such as Google, Baidu, Microsoft and Facebook, much of the additional waves of value creation will go beyond the software sector.

This AI Transformation Playbook draws on insights gleaned from leading the Google Brain team and the Baidu AI Group, which played leading roles in transforming both Google and Baidu into great AI companies. It is possible for any enterprise to follow this Playbook and become a strong AI company, though these recommendations are tailored primarily for larger enterprises with a market cap from $500M to $500B.

These are the steps I recommend for transforming your enterprise with AI, which I will explain in this playbook:

1. **Execute pilot projects to gain momentum**
2. **Build an in-house AI team**
3. **Provide broad AI training**
4. **Develop an AI strategy**
5. **Develop internal and external communications**

[1] https://www.mckinsey.com/featured-insights/artificial-intelligence/notes-from-the-ai-frontier-modeling-the-impact-of-ai-on-the-world-economy

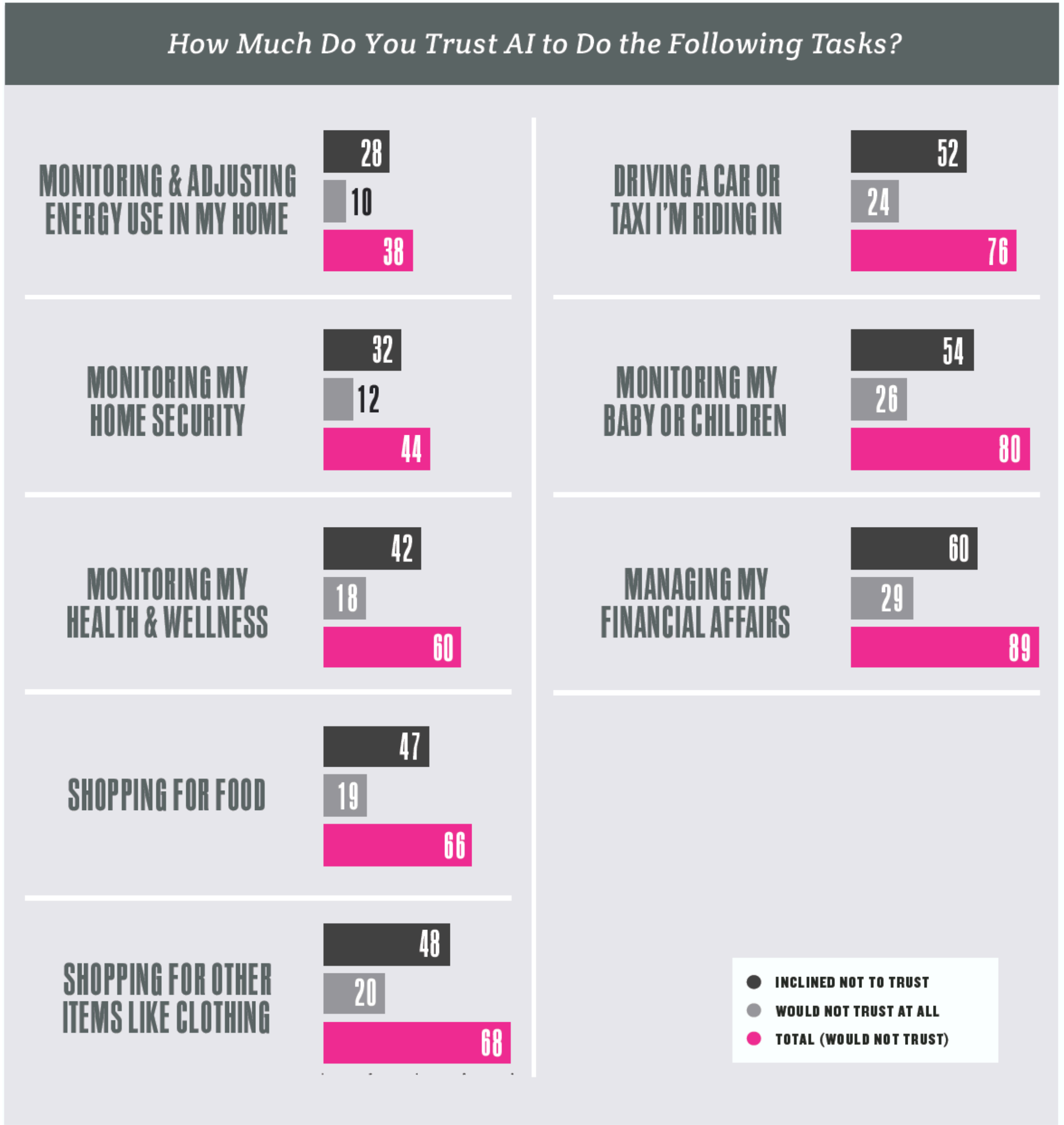
1 LANDING AI Andrew Ng

AI Ethics

If a person knows nothing about how an algorithm is designed, they will think that the answer they get out of technology is right. The more you know about how algorithms work, the more you understand how subjective they are, but everyone should keep in mind that algorithms have biases as they are designed by people.

Dr. Fiona Kerr, Founder and MD, The NeuroTech Institute, sparks and honey Advisory Board member

AI Ethics



Source: Accenture Strategy

AI Ethics

COMPLAINTS ABOUT POORLY CONSTRUCTED ALGORITHMS

@rob__s December 4, 2018

Ad profiling can be so bad.

- I put my iPad on my parents' WiFi and now Amazon is giving me crazy recommendations.

- Pinterest thinks I want claret bridesmaid dresses.

Neither based on my browsing behaviour. Crude, IP-based.

It betrays privacy, and maybe even Christmas gifts.

CURIOSITY ABOUT THE ORIGINS OF RECOMMENDATIONS

@_d__h December 8, 2018

Based on my Netflix picks someone at Netflix probably thinks I'm a convicted felon.

POINTING OUT WEIRD THINGS SOCIAL PLATFORMS THINK YOU LIKE

@amanda__r December 20, 2018

Things @Facebook thinks I'm interested in:

-1st person games

-Swing bowling ???

-Quartz (the rock)

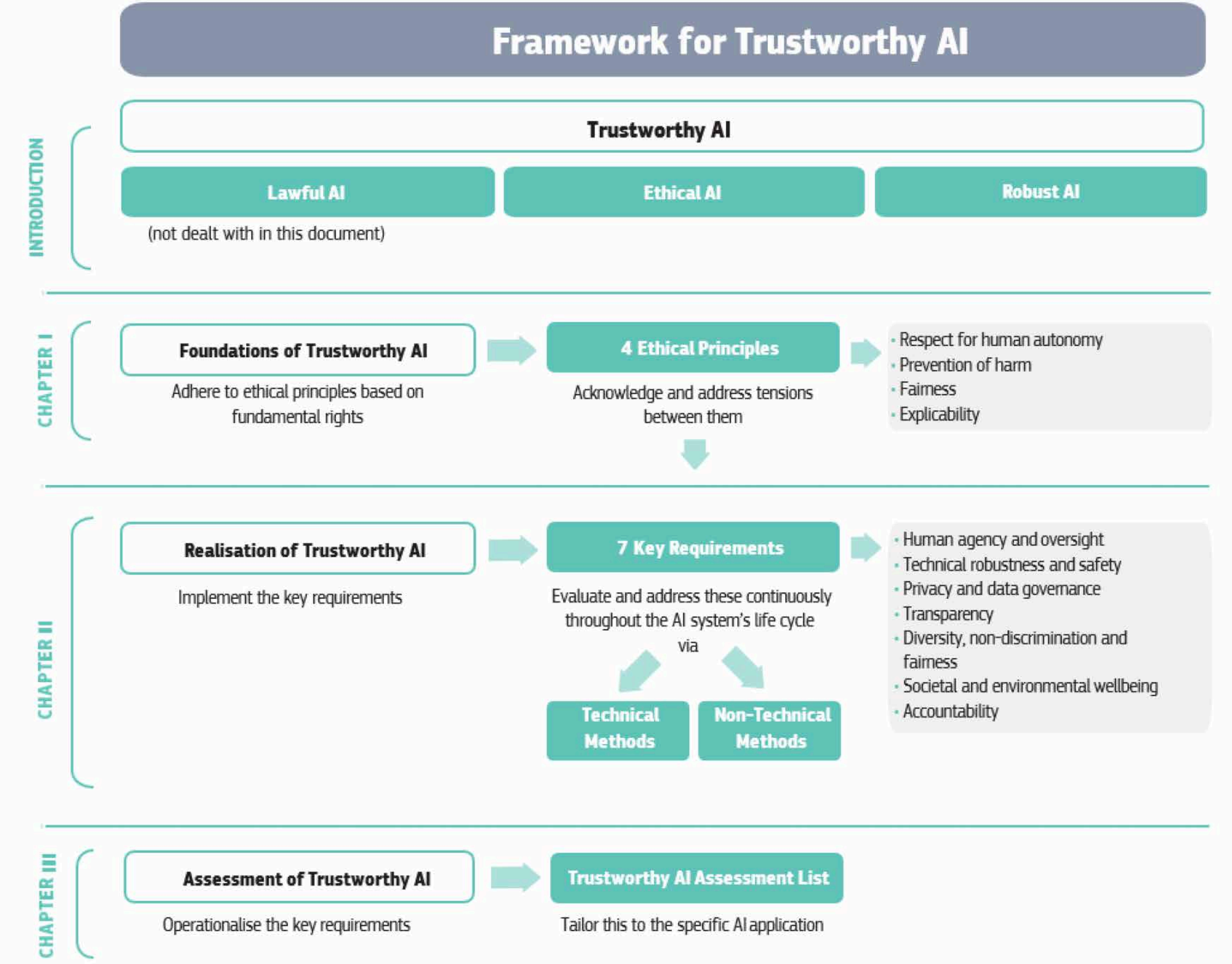
-Lead (the metal)

-Chapters... just, in general

-Conquistador Hernán Cortés

-Annapolis, Maryland

AI Ethics: European Commission



HumAIn Podcast

Podcast, Season 1 // May 7, 2019

How the World can Participate in AI (feat. Tara Chklovski)

00:00 40:30

Tara Chklovski from Iridescent shares about the AI Family Challenge, lifelong learning, Technovation, and how the world can participate in AI.

Podcast, Season 1 // April 30, 2019

Exploring the Future of AI (feat. Jed Dougherty)

00:00 45:19

In this episode, I sit down with Jed Dougherty to talk about the future of AI and why he likes hiring people from the humanities.

HumAIn Podcast

www.humainpodcast.com

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