University of Ljubljana, Faculty of Computer and Information Science

Intelligent Sytems

Prof Dr Marko Robnik-Šikonja



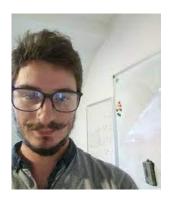
Lecturer

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- (01) 4798 241
- Contact hour (see webpage)
 - currently, Wednesdays, 11:00 -12:00; for other times or video connection, email me
- **Research interests**: machine learning, artificial intelligence, natural language processing, network analytics, data science, data mining, algorithms and data structures
- Teaching: several courses from the area of data mining, algorithms, machine learning, and natural language processing
- **Software:** an author of three open source R packages from the area of predictive modelling and data analytics (CORElearn, semiArtificial, ExplainPrediction)



Assistants

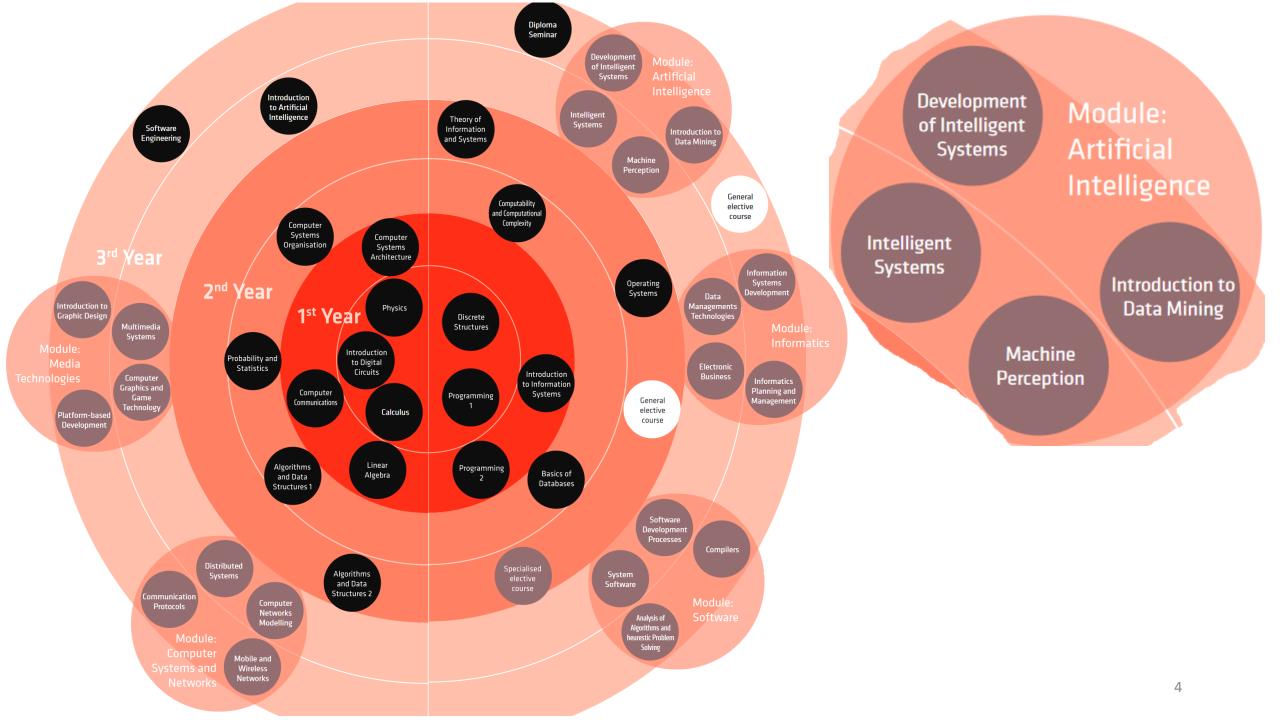
Blaž Škrlj, PhD student



• Tadej Škvorc, PhD student



• tutorials, assignments, work in R please, prepare questions!



Syllabus

- nature inspired computing (genetic algorithms, genetic programming, ant colony optimization)
- basics of machine learning,
- similarity based learning, kNN
- decision rules and subgroup discovery
- ensemble methods
- support vector machines
- neural networks
- reinforcement learning
- natural language processing
- multiagent systems

Objectives

- students shall become acquainted with
 - nature inspired computing
 - machine learning
 - model selection and evaluation techniques
 - model comprehensibility and explanation
 - practical application of predictive modeling in R programming language and environment
 - natural language processing
 - reinforcement learning
 - multiagent systems
- practical use of theoretical knowledge on (almost) real-world problems
- awareness of domain expertise and ethical issues in data science
- increase the (mental) problem-solving toolbox with
 - predictive modeling techniques
 - reinforcement learning
 - result understanding, visualization and explanation approaches
- for a given prediction problem students shall be able to
 - transform it to a form suitable for predictive modeling
 - select and train an appropriate predictive model
 - evaluate the model and present the results in a comprehensible form and language.

Odd-one out



Be able to explain

- difference between different types of machine learning models
- properties of models: bias, variance, generalization, hypothesis language
- properties of the following models: kNN, decision rules, bagging, boosting, random forests, stacking, SVM, neural networks
- properties and purpose of evaluation approaches and metrics: cross-validation, bootstrapping, ROC curves, sensitivity, specificity etc.
- inference methods for predictive methods and explanation of predictions
- when and why to apply reinfocement learning
- how to prepare and process text in a text mining
- when and how and to optimize a problem using genetic algorithms

Build and evaluate models in R

- visualize the data set and created models
- prepare data into a suitable form suitable for modeling algorithms
- apply classification and regression models to solve a prediction task with a given data set
- estimate error of models using statistically valid approaches
- select models and tune their parameters using cross-validation and bootstrapping
- visualize models and explain their predictions
- given a new data set select appropriate modeling technique and evaluate the created model

Why R?

• IEEE Spectrum 2019 list of popular programming languages

Rank	Language	Type				Score
1	Python	#		Ç	0	100.0
2	Java	#	0	Ç		96.3
3	С		0	Ç	0	94.4
4	C++		0	Ģ	0	87.5
5	R			Ç		81.5
6	JavaScript	#				79.4
7	JavaScript C#	#	0	Ç	0	79.4 74.5
			0		0	
7	C#		0		•	74.5

Nature inspired computing

- genetic algorithms
- genetic programming
- ant colony optimization

Introduction to statistical predictive modelling

- Learning as modelling: data, evidence, background knowledge, predictive models, hypotheses, learning as optimization, learning as search, criteria of success, inductive learning, generalization.
- Classification and regression: supervised and unsupervised learning, learning discrete and numeric functions, learning relations, learning associations.
- Simple classification models: nearest neighbor, decision rules

Model selection

- Bias and variance: error decomposition, trade-off, estimating bias and variance
- Generalization performance: training and testing set error, cross-validation, evaluation set, bootstrapping.
- Performance measures: confusion matrix, sensitivity and specificity, ROC curves, AUC, cost-based classification.
- Parameter tuning: regularization, MDL principle.
- Calibration of probabilities: binning, isotonic regression.
- No free lunch theorem.

Ensemble methods

- Model averaging, why ensembles work.
- Tree based ensembles: bagging, boosting, random forests.
- MARS and AODE ensembles.
- Stacking.

Kernel methods

- SVM for classification and regression: kernels, support vectors, hyperplanes.
- SVM for more than two classes: one vs. one, one vs. all.

Neural networks

- perceptron,
- backpropagation,
- RBF networks,
- setting structure of networks
- deep neural networks
- autoencoders
- GANs
- the role of embeddings

Explaining prediction models

- Model comprehensibility, visualization and knowledge discovery.
- General methodology for explaining predictive models.
- Model level and instance level explanations, methods SHAP, LIME, EXPLAIN, and IME.

Learning with special settings

- imbalanced data,
- multi-task learning,
- multi-label learning.

Reinforcement learning

- basics
- Markov decision problem
- Q learning

Natural language processing

- text preprocesing
- text representation
- text similarity
- text classification
- sentiment analysis

Multiagent systems

- types of agents
- agent architectures
- distributed constraint satisfaction
- distributed path finding

Obligations

- 5 quizzes
- three projects, 50 points
- written exam, 50 points

Grading

Obligation	% of total	subject to
Five quizzes	0%	≥ 50% alltogether
Three projects	50%	≥ 50% each
Written exam	50%	≥ 50%

Learning materials

- learning materials in the eClassroom
- slides
- links to textbook and papers
- R code and examples
- links to data sets
- install the open-source systems R and RStudio

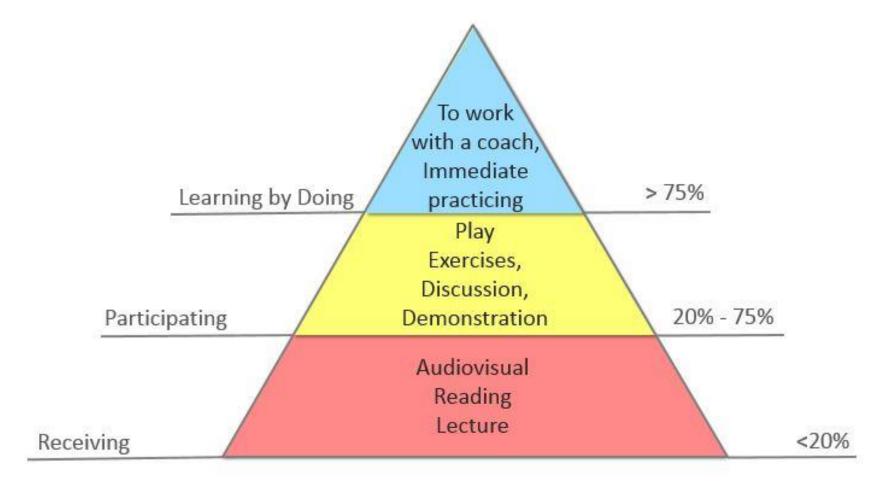
Readings

- James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013).
 An introduction to statistical learning with applications in R. Springer, New York.
 - freely available from authors' homepages
 - also code and slides from authors and Abbass Al Sharif (some used in this course)

Further readings:

- Friedman, J., Hastie, T., & Tibshirani, R. (2001). The elements of statistical learning.
 Springer, Berlin.
- Ian Goodfellow, Yoshua Bengio, and Aaron Courville (2016). *Deep Learning*. MIT press, freely available from authors' homepages
- François Chollet (2017). Deep Learning with Python. Manning.
- Kononenko, I., Robnik-Šikonja, M.: Inteligentni sistemi. Založba FE in FRI, 2010 (in Slovene)
- scientific papers
- many excellent machine learning and data mining courses on Coursera and edX

BTW: retention of learning



Retention of Learning

Data Science

- good job perspective
- Forbes list of the most promising jobs in the USA

Top 10 Best Jobs in America in 2020

Rank	Job Title	Median Base Salary	Job Satisfaction	Job Openings
1	Front End Engineer	\$105,240	3.9	13,122
2	Java Developer	\$83,589	3.9	16,136
3	Data Scientist	\$107,801	4.0	6,542
4	Product Manager	\$117,713	3.8	12,173
5	Devops Engineer	\$107,310	3.9	6,603
6	Data Engineer	\$102,472	3.9	6,941
7	Software Engineer	\$105,563	3.6	50,438
8	Speech Language Pathologist	\$71,867	3.8	29,167
9	Strategy Manager	\$133,067	4.3	3,515
10	Business Development Manager	\$78,480	4.0	6,560

Source: Glassdoor Economic Research (Glassdoor.com/research)

• Thomas H. Davenport, D.J. Patil: Data Scientist: The Sexiest Job of the 21st Century. Harvard Business Review, October 2012

MODERN DATA SCIENTIST

Data Scientist, the sexiest job of the 21th century, requires a mixture of multidisciplinary skills ranging from an intersection of mathematics, statistics, computer science, communication and business. Finding a data scientist is hard. Finding people who understand who a data scientist is, is equally hard. So here is a little cheat sheet on who the modern data scientist really is.

MATH & STATISTICS

- ☆ Machine learning
- ☆ Statistical modeling
- ☆ Experiment design
- ☆ Bayesian inference
- Supervised learning: decision trees, random forests, logistic regression
- Unsupervised learning: clustering, dimensionality reduction
- □ Optimization: gradient descent and variants

GE

PROGRAMMING & DATABASE

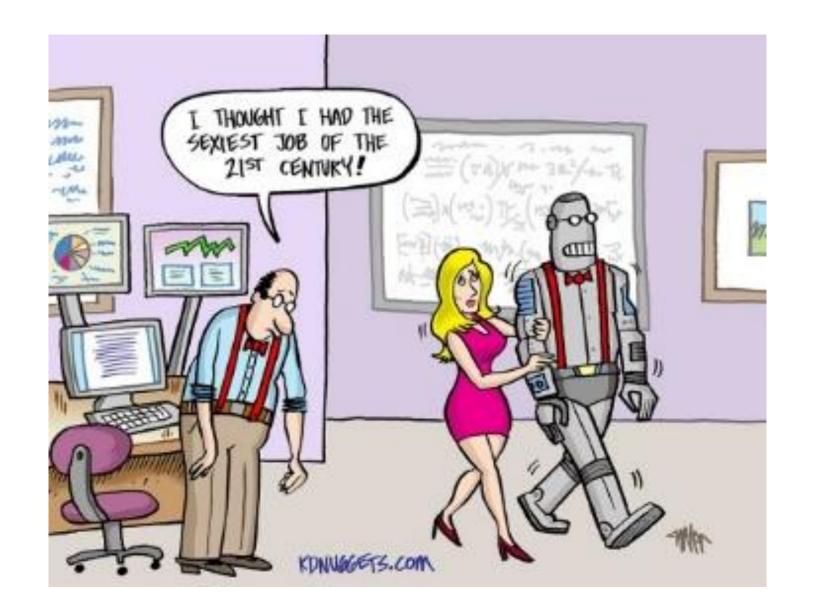
- ☆ Computer science fundamentals
- ☆ Scripting language e.g. Python
- ☆ Statistical computing packages, e.g., R.
- ☆ Databases: SOL and NoSOL
- ☆ Relational algebra
- Parallel databases and parallel query processing
- ☆ MapReduce concepts
- ☆ Hadoop and Hive/Pig
- ☆ Custom reducers
- ☆ Experience with xaaS like AWS

COMMUNICATION & VISUALIZATION

- ☆ Able to engage with senior management
- ☆ Story telling skills
- ☆ Translate data-driven insights into decisions and actions
- ☆ Visual art design
- ☆ R packages like ggplot or lattice
- ☆ Knowledge of any of visualization tools e.g. Flare, D3.js, Tableau

DOMAIN KNOWLEDGE & SOFT SKILLS

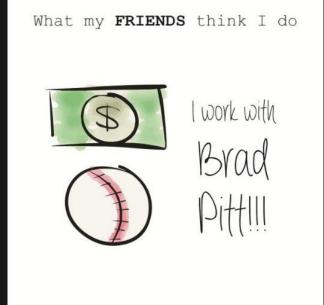
- ☆ Passionate about the business
- ☆ Curious about data
- ☆ Influence without authority
- ☆ Hacker mindset
- ☆ Problem solver
- Strategic, proactive, creative, innovative and collaborative

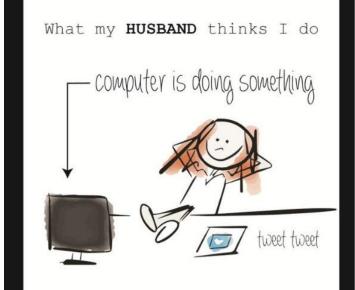


DATA SCIENTIST





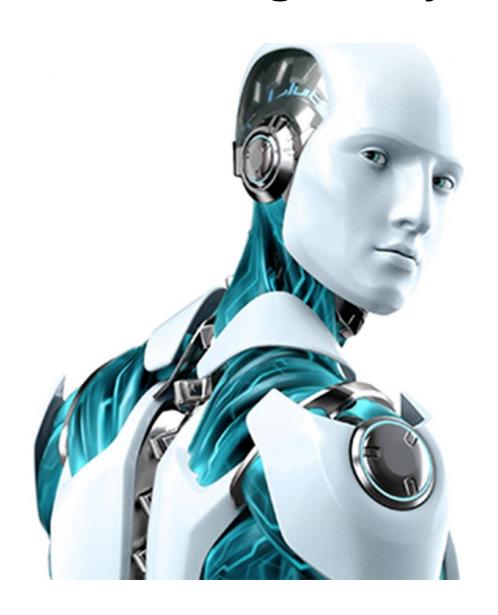








Intelligent systems and media



Will robots destroy us?

Will they take our jobs?

Will we still need a driving licence?

Will we still need doctors?

How will humanoid robots evolve?

What about cyborgs?

What is artificial general intelligence?

What is technological singularity?

New prophets of tehnological singularity

Elon Musk says humans must become cyborgs to stay relevant. Is he right?

Sophisticated artificial intelligence will make 'house cats' of humans, claims the entrepreneur, but his grand vision for mind-controlled tech may be a long way off





Some scientific responses

- Rodney Brooks: The Seven Deadly Sins of Predicting the Future of AI.
 https://rodneybrooks.com/the-seven-deadly-sins-of-predicting-the-future-of-ai/ tudi MIT Technology Review
- Marko Robnik-Šikonja: Is artificial intelligence a (job) killer?. The Conversation, Jul. 2017 https://theconversation.com/is-artificial-intelligence-a-job-killer-80473

• ...



Short history of optimism

- starting in 1950s,
 1956 Dartmouth conference
- great expectations, enormous underestimation of problem difficculty
- Al winter (2 x)



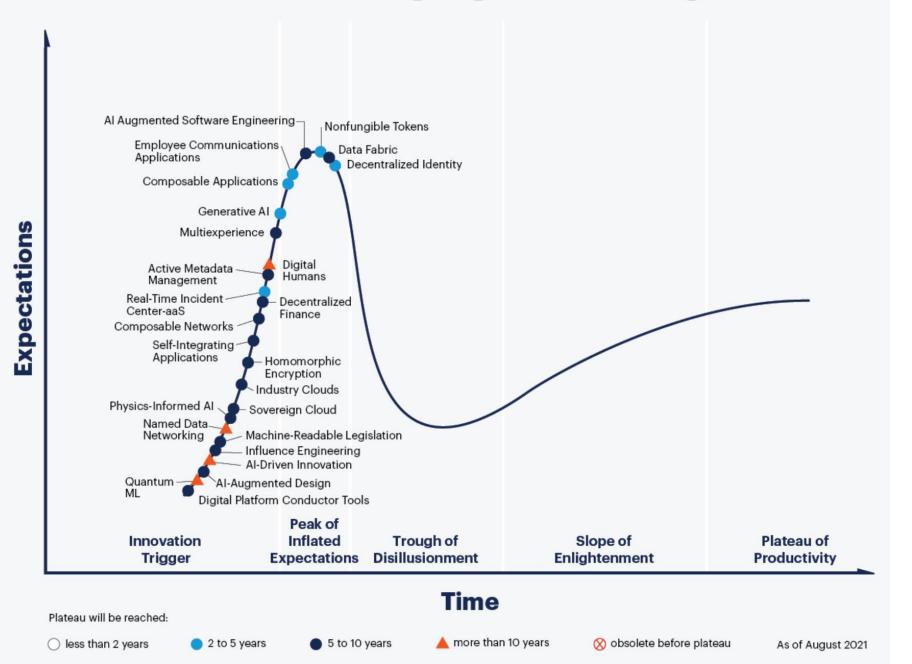
1958, H. A. Simon and Allen Newell: "... within ten years a digital computer will discover and prove an important new mathematical theorem."

1965, H. A. Simon: "... machines will be capable, within twenty years, of doing any work a man can do."

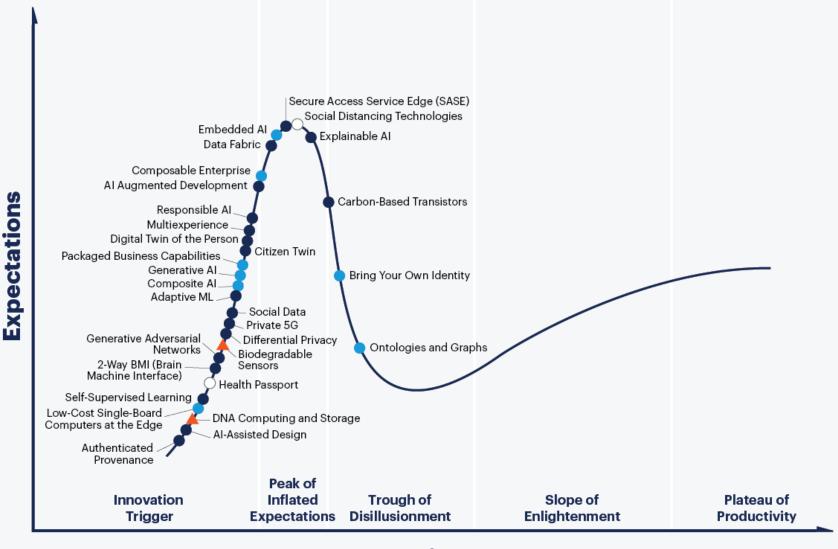
1967, Marvin Minsky: "Within a generation ... the problem of creating 'artificial intelligence' will substantially be solved."

1970, Marvin Minsky: "In from three to eight years we will have a machine with the general intelligence of an average human being."

Hype Cycle for Emerging Technologies, 2021



Hype Cycle for Emerging Technologies, 2020



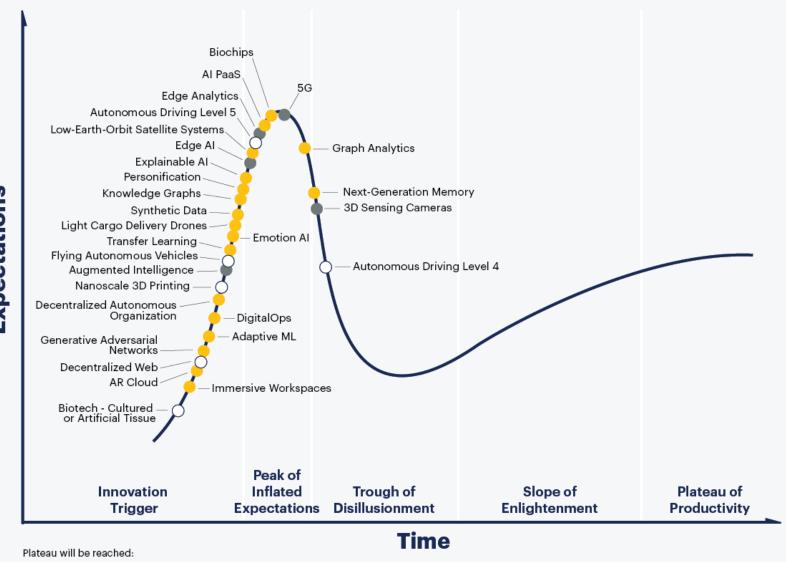
Time

As of July 2020

Oless than 2 years

2 to 5 years

Gartner Hype Cycle for Emerging Technologies, 2019



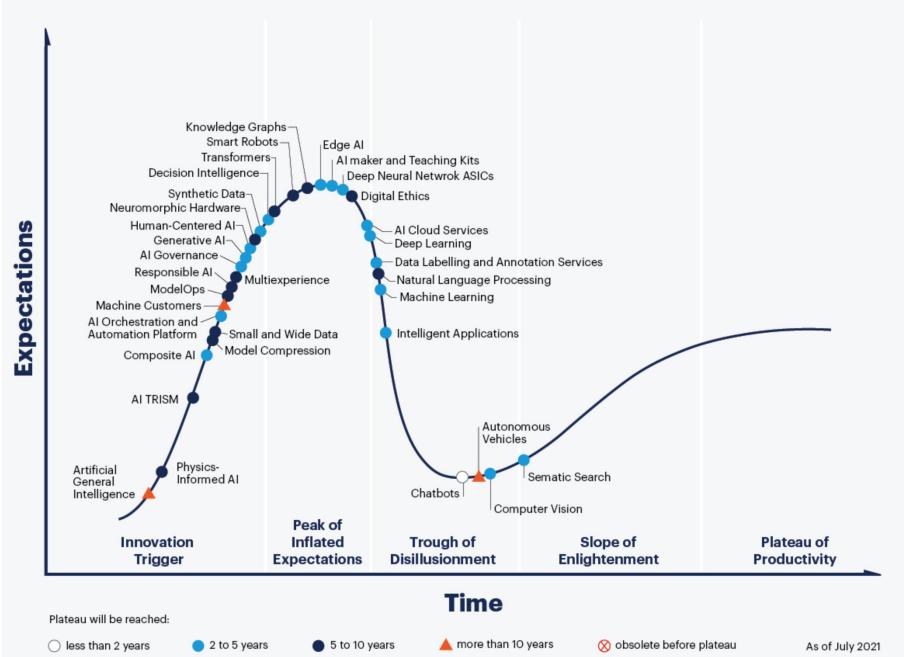
5 to 10 years

more than 10 years

obsolete before plateau

As of August 2019

Hype Cycle for Artificial Intelligence, 2021



Hype Cycle for Artificial Intelligence, 2020

