

100 Days Of Machine Learning Code

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According to the challenge we are going to explore a project and maybe the possibility to monetize a solution of an industry problem using ML.

URL

"Who's ready to take the 100 days of ML code challenge? That means coding machine learning for at least an hour everyday for the next 100 days. Pledge with the #100DaysOfMLCode hashtag, I'll give the first few winners a shoutout!"

I. 100DAYSOFMLCODESFMB

After read this tweet can be a great way to master something, do not know what is, yet.

In day 2 I decided to explore the MIT course **9.520/6.860: Statistical Learning Theory and Applications** Fall 2017.

II. DAY 1 [THU JUL 5 20:58:13 CDT 2018]

A. Siraj Raval Tweet

Who's ready to take the 100 days of ML code challenge? That means coding machine learning for at least an hour everyday for the next 100 days. Pledge with the #100DaysOfMLCode hashtag, I'll give the first few winners a shoutout!

Link to Tweet.

B. Challenge

Pick an industry that sounds exciting, find a problem they have, think about how AI could be applied to that problem, locate a relevant dataset, apply AI to the dataset, monetize the solution.

C. Following my own path using Julia, R and Python

In that order, trying to go as far as I can using the first one syntax.

D. Problem Sets

Problem Set 1 Problem Set 2 Problem Set 3 Problem Set 4

Submission instructions: Follow the instructions included with the problem set. Use the latex template for the report (there is a maximum page limit). Submit your report online through `stellar.mit` by the due date/time and a printout in the first class after the due date.

E. Projects

Reports are 1-page, extended abstracts using NIPS style files.

1) *Projects archive*: List of Wikipedia entries, created or edited as part of projects during previous course offerings.

F. Syllabus

URL.

Follow the link for each class to find a detailed description, suggested readings, and class slides. Some of the later classes may be subject to reordering or rescheduling.

Class	Date	Title	Instructor(s)
Class 01	Wed Sep 06	The Course at a Glance	TP
Class 02	Mon Sep 11	The Learning Problem and Regularization	LR
Class 03	Wed Sep 13	Reproducing Kernel Hilbert Spaces	LR
Class 04	Mon Sep 18	Positive Definite Functions, Feature Maps and Mercer Theorem	LR
Class 05	Wed Sep 20	Tikhonov Regularization and the Representer Theorem	LR
Class 06	Mon Sep 25	Logistic Regression and Support Vector Machines	LR
Class 07	Wed Sep 27	Regularized Least Squares	LR
Class 08	Mon Oct 02	Iterative Regularization via Early Stopping	LR
Class 09	Wed Oct 04	Learning with Stochastic Gradients	LR
Class 10	Wed Oct 11	Large Scale Kernel Methods	LR
Class 11	Mon Oct 16	Sparsity Based Regularization	LR
Class 12	Wed Oct 18	Convex Relaxation and Proximal Gradient	LR
Class 13	Mon Oct 23	Structured Sparsity Regularization	LR
Class 14	Wed Oct 25	Multiple Kernel Learning	LR
Class 15	Mon Oct 30	Learning Theory	LR
Class 16	Wed Nov 01	Generalization Error and Stability	LR
Class 17	Mon Nov 06	Online Learning II	Sasha Rakhlin
Class 18	Wed Nov 08	Online Learning II	Sasha Rakhlin
Class 19	Mon Nov 13	Data Representation by Design	GE
Class 20	Wed Nov 15	Learning Data Representation: Dictionary Learning	GE
Class 21	Mon Nov 20	Learning Data Representation: Neural Networks	GE
Class 22	Wed Nov 22	Deep Learning Theory: Approximation	TP
Class 23	Mon Nov 27	Deep Learning Theory: Optimization	TP
Class 24	Wed Nov 29	Deep Learning Theory: Generalization	TP
Class 25	Mon Dec 04	Learning Data Representation: Invariance and Selectivity	TP
Class 26	Wed Dec 06	Deep Networks and Visual Cortex	TP
Class 27	Mon Dec 11	Poster presentations (2 sessions)	

G. Class 1. Course at a Glance

1) *Description*: We introduce and motivate the main theme of much of the course, setting the problem of supervised learning from examples as the ill-posed problem of approximating a multivariate function from sparse data. We present an overview of the theoretical part of the course and sketch the connection between classical Regularization Theory with its RKHS-based algorithms and Learning Theory. We briefly describe several different applications ranging from vision to computer graphics, to finance and neuroscience. The last third of the course will be on data representations for learning and deep learning. It will introduce recent theoretical developments towards a) understanding why deep learning works and b) a new phase in machine learning, beyond classical supervised learning: how to learn in an unsupervised way representations that significantly decrease the sample complexity of a supervised learning.

2) *Slides*:

- Slides for this lecture: PDF.

a) *Youtube video class 2015.*: [href6AWZS4Ho2Z8](https://www.youtube.com/watch?v=6AWZS4Ho2Z8)video

Link here

b) *2017 Course – Center for Brains, Minds and Machines (CBMM)*: [hrefQ5itLKscYT](https://www.youtube.com/watch?v=Q5itLKscYT)video

Link here

3) *Relevant Reading:*

- Mnih et. al. (Deep Mind), Human-level control through deep reinforcement learning, Nature 518, pp. 529–533, 2015.
- Nature Insights, Machine Intelligence (with review article on Deep Learning), Nature, Vol. 521 No. 7553, pp. 435–482, 2015.

IV. DAY 3 [SAT JUL 7 13:12:57 CDT 2018]

- 1) Class 1 video [14.51]
- 2) Slide [26]

V. DAY 4 [SUN JUL 8 12:59:19 CDT 2018]

- 1) Class 1 Done

VI. DAY 5 [MON JUL 9 16:12:01 CDT 2018]

A. *Math camp*

Math camp extra class, optional for those interested: Tue. 09/12, 4:00 pm – 5:30 pm, Singleton auditorium (46–3002).

1) *Description:* We review the basic prerequisites for the course on functional analysis, linear algebra, probability theory and concentration of measure.

2) *Class Reference Material:*

a) *Youtube video:* [hrefAsogCoscZgEvideo](#)

Link here

b) *Local video:* Video file.

c) *Slides:* Slides: PDF. Original URL. Notes/Book appendix: PDF. Original URL.

3) *Some concept testing with data:* We like \mathbb{R}^D because we can

Addition

[5, 7, 9]

Multiply by numbers

[3, 6, 9]

Scalar product

[1, 2, 3]

[4, 5, 6]

32

32

Norm

3.7416573867739413

3.7416573867739413

3.7416573867739413

Distances between vectors

5.196152422706632

5.196152422706632

RMS value

2.160246899469287

Standard deviation

Important note: Julia do not use this definition.

0.8164965809277261

Julia's way:

1.0

Angle between two vectors

0.2257261285527342

This what we called "Euclidean" structure. We want to do the something with $D = \infty$

4) *Cauchy-Schwarz inequality*: $\langle v, w \rangle \leq \langle v, v \rangle^{\frac{1}{2}} \langle w, w \rangle^{\frac{1}{2}}$.

:: v and w inner product ::

32

:: must be less or equal to ::

32.83291031876401

VII. DAY 6 (PENDING)

A. 9.520/6.860, Class 02

1) *Description*: We formalize the problem of learning from examples in the framework of statistical learning theory and introduce key terms and concepts such as loss functions, empirical and excess risk, generalization error and consistency. We briefly describe foundational results and introduce the concepts of hypothesis space and regularization.

2) *Class Reference Material*: L. Rosasco, T. Poggio, **Machine Learning: a Regularization Approach**, MIT-9.520 Lectures Notes, Manuscript, Dec. 2017.

3) *Chapter 1 – Statistical Learning Theory*: Note: The course notes, in the form of the circulated book draft is the reference material for this class. Related and older material can be accessed through previous year offerings of the course.

4) *Further Reading*:

- F. Cucker and S. Smale, On the mathematical foundations of learning, Bulletin of the American Mathematical Society, 2002.
- T. Evgeniou, M. Pontil and T. Poggio, Regularization networks and support vector machines, Advances in Computational Mathematics, 2000.
- S. Villa, L. Rosasco and T. Poggio, On learnability, complexity and stability, "Empirical Inference, Festschrift in Honor of Vladimir N. Vapnik." Springer-Verlag, Chapter 7, 2013.
- V. Vapnik, An overview of statistical learning theory, IEEE Trans. on Neural Networks, 10(5), 1999.

5) *Video*: [hrefSFxypsvhhMQvideo](#)

[Link here](#)

VIII. REFERENCES

- 1) Introductory Machine Learning Notes. Lorenzo Rosasco, MIT, 2017. Original URL.