# Machine Learning for Cities

Prof. Luis Gustavo Nonato

NYU / CUSP - GX 5006

January 24, 2017

# Course Structure

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## Content

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- Principal Component Analysis

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Data Science Central

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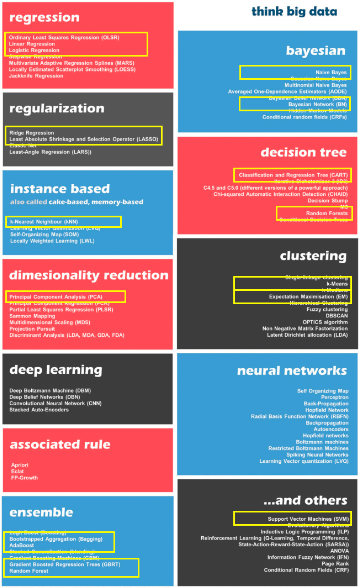

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CUSP-GX-5006-classesmaterial.pdf will be updated every week !!

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If a team is not able to find a theme/problem I can suggest one.

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No deep knowledge about python will be required.

The code will be as simple as possible and easily understandable, even for students not so experienced in computer programming.

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It is assumed that there is a "hidden" model/process capable of analyzing the content of an email and then decides whether it is a spam or not.

The goal is to *learn* the hidden model/process from data !!

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The taxonomy above is simplistic, there are methods that do not properly fit in any of those two categories, as for example semi-supervised and reinforcement learning methods.

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- This course covers important concepts and machine learning techniques
- There are, though, relevant not coved topics (Neural Networks for instance)
- We will adopt a very practical approach, with real data and applications.