Introduction to *Urban* Data Science

Introduction-II

(EPA1316)

Lecture 1

Trivik Verma

Last Time

- Introduction to the Course
- The (Geo-)Data Revolution
- (Geo-)Data Science
- Tools - Python and Conda

Today

- Why Data Science?
- What is Data Science?
- Examine the **role** of evidence in policy
- Analyse **data** understanding and preparation **requirements**

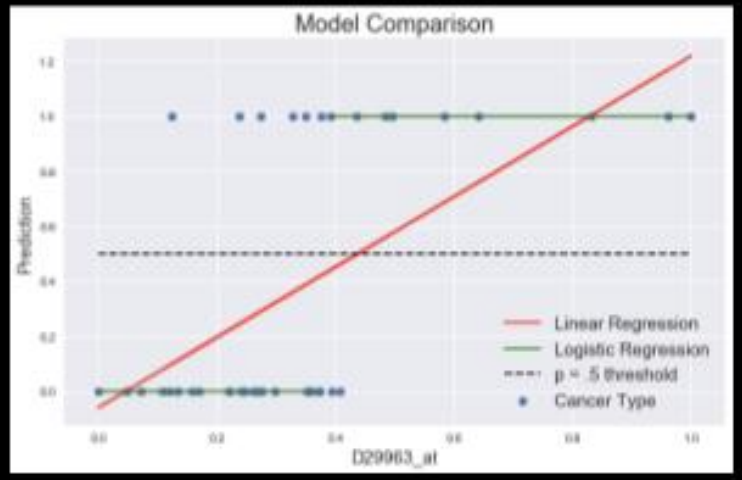
Why Data Science?

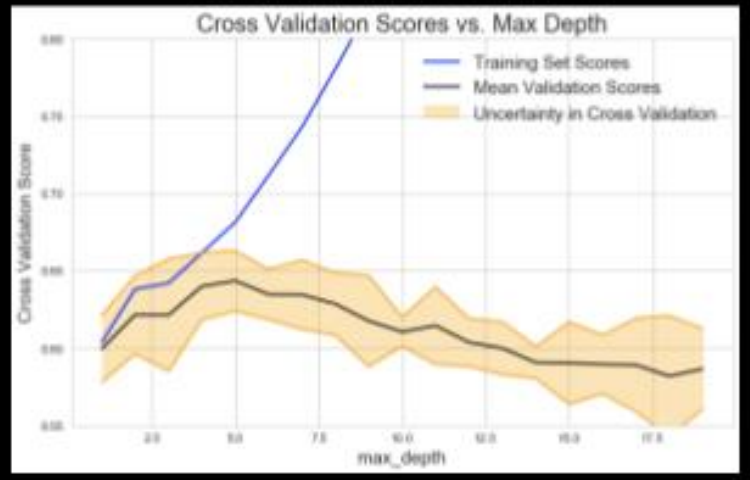
what my friends think I do

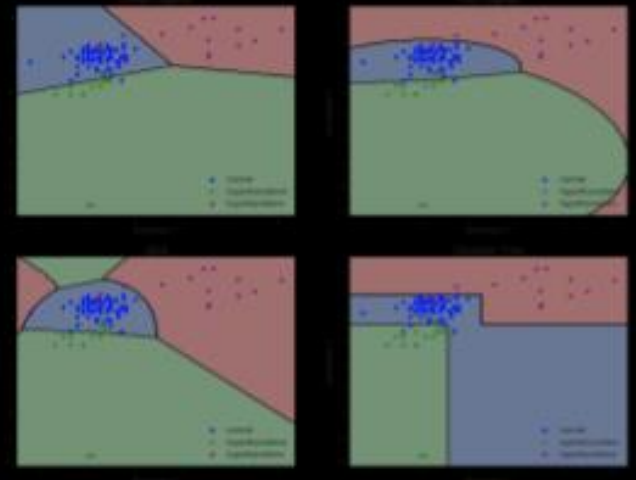
what my family thinks I do

what society thinks I do

what I actually (will) do in Data Science 1







History

Long time ago (thousands of years) science was only empirical, and people counted stars

History (cont)

Long time ago (thousands of years) science was only empirical, and people counted stars or crops

History (cont)

Long time ago (thousands of years) science was only empirical, and people counted stars or crops and used the data to create machines to describe the phenomena

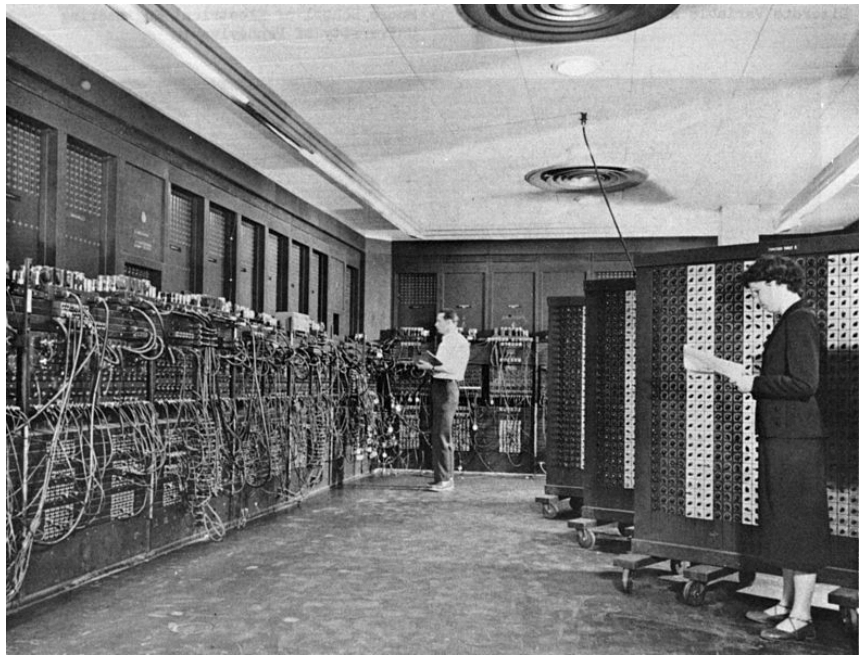
History (cont)

Few hundred years: theoretical approaches, try to derive equations to describe general phenomena.

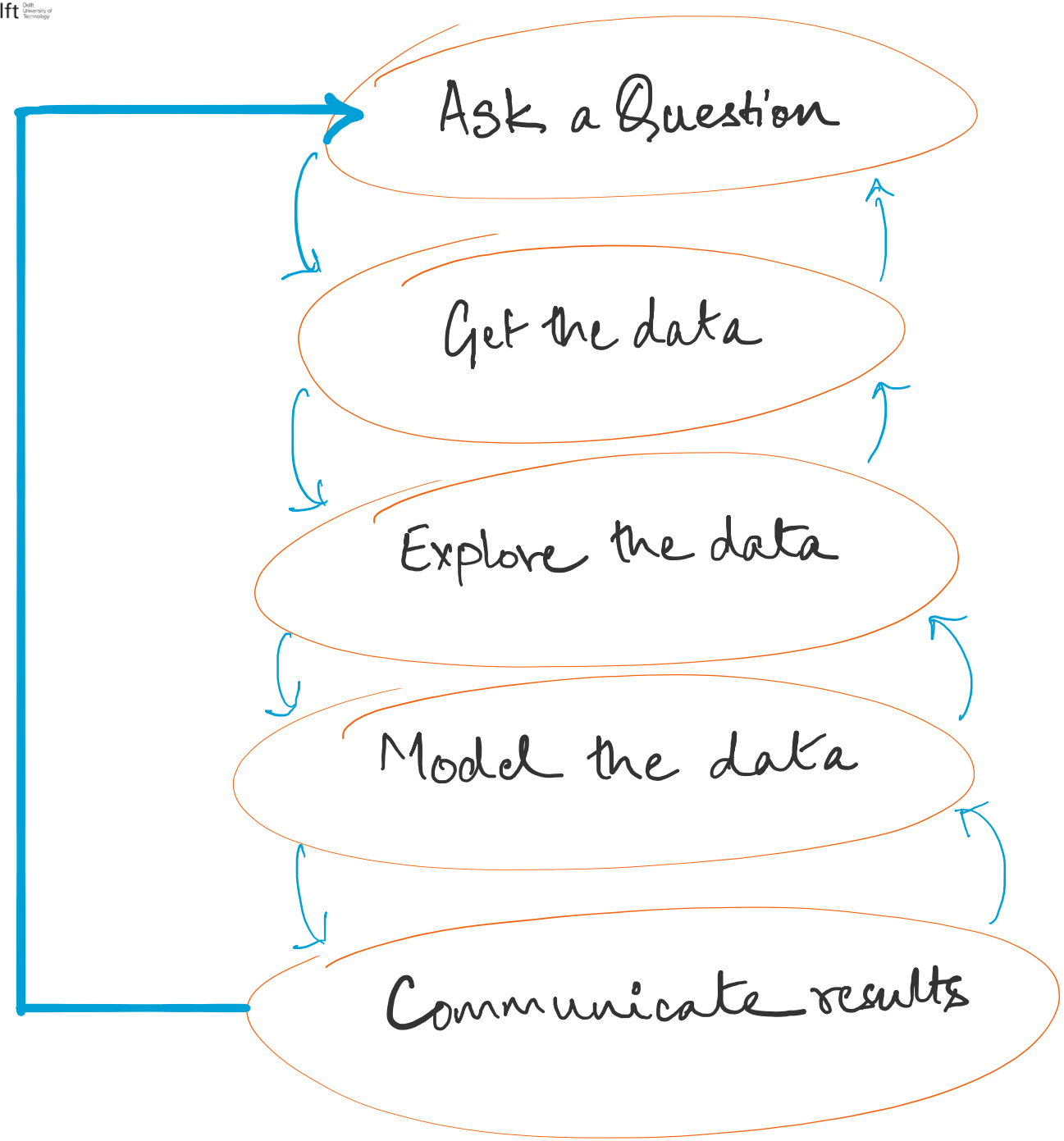
Maxwell's Equations	$\nabla \cdot \mathbf{E} = 0 \quad \nabla \cdot \mathbf{H} = 0$ $\nabla \times \mathbf{E} = -\frac{1}{c}\frac{\partial \mathbf{H}}{\partial t} \quad \nabla \times \mathbf{H} = \frac{1}{c}\frac{\partial E}{\partial t}$	J.C. Maxwell, 1865
Second Law of Thermodynamics	$\mathrm{d}S \geq 0$	L. Boltzmann, 1874
Relativity	$E = mc^2$	Einstein, 1905
Schrodinger's Equation	$i\hbar\frac{\partial}{\partial t}\Psi = H\Psi$	E. Schrodinger, 1927
Information Theory	$H = -\sum p(x) \log p(x)$	C. Shannon, 1949
Chaos Theory	$x_{t+1} = kx_t(1 - x_t)$	Robert May, 1975
Black-Scholes Equation	$\frac{1}{2}\sigma^2 S^2 \frac{\partial^2 V}{\partial S^2} + rS\frac{\partial V}{\partial S} + \frac{\partial V}{\partial t} - rV = 0$	F. Black, M. Scholes, 1990

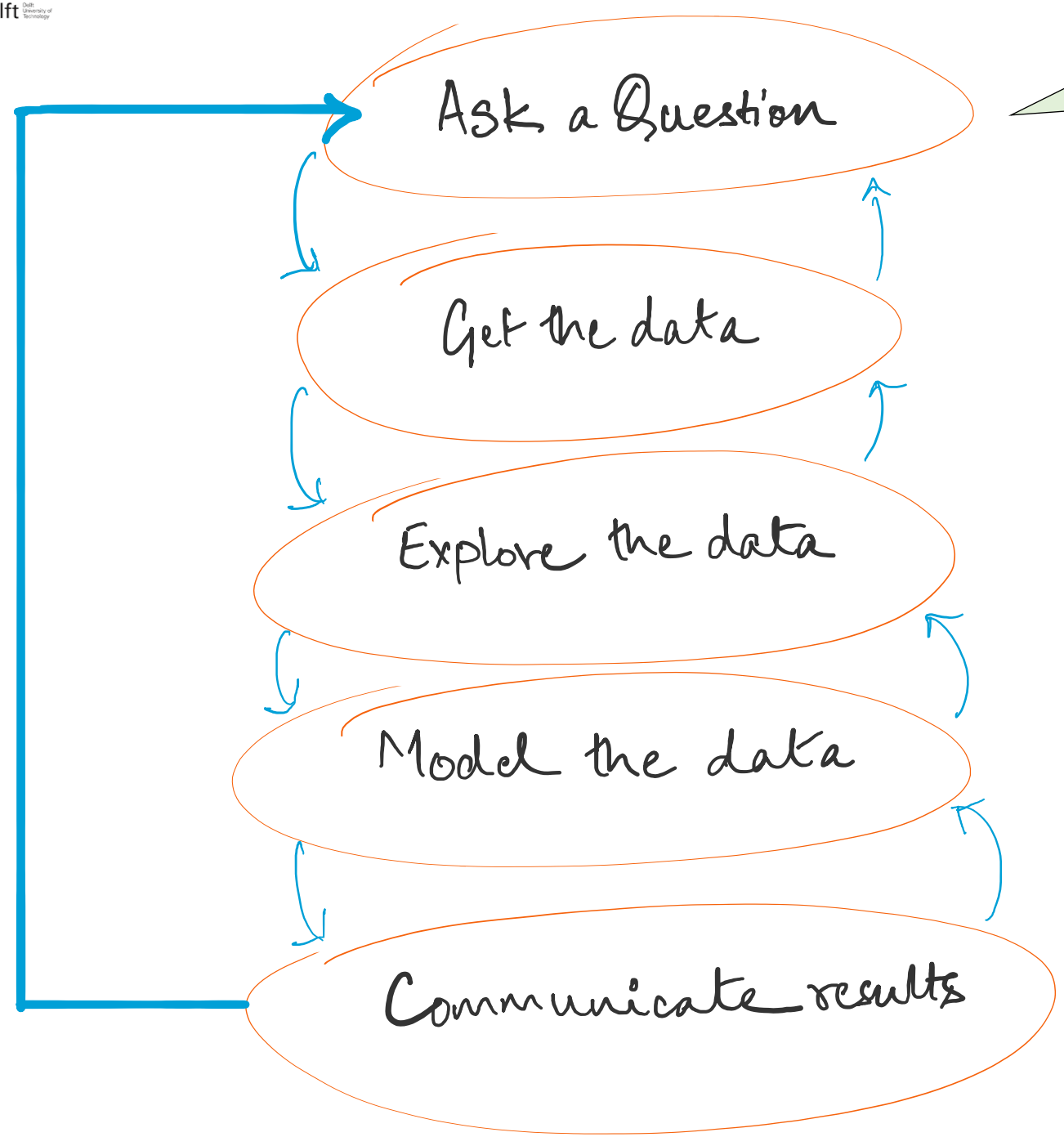
History (cont)

About a hundred years ago: computational approaches

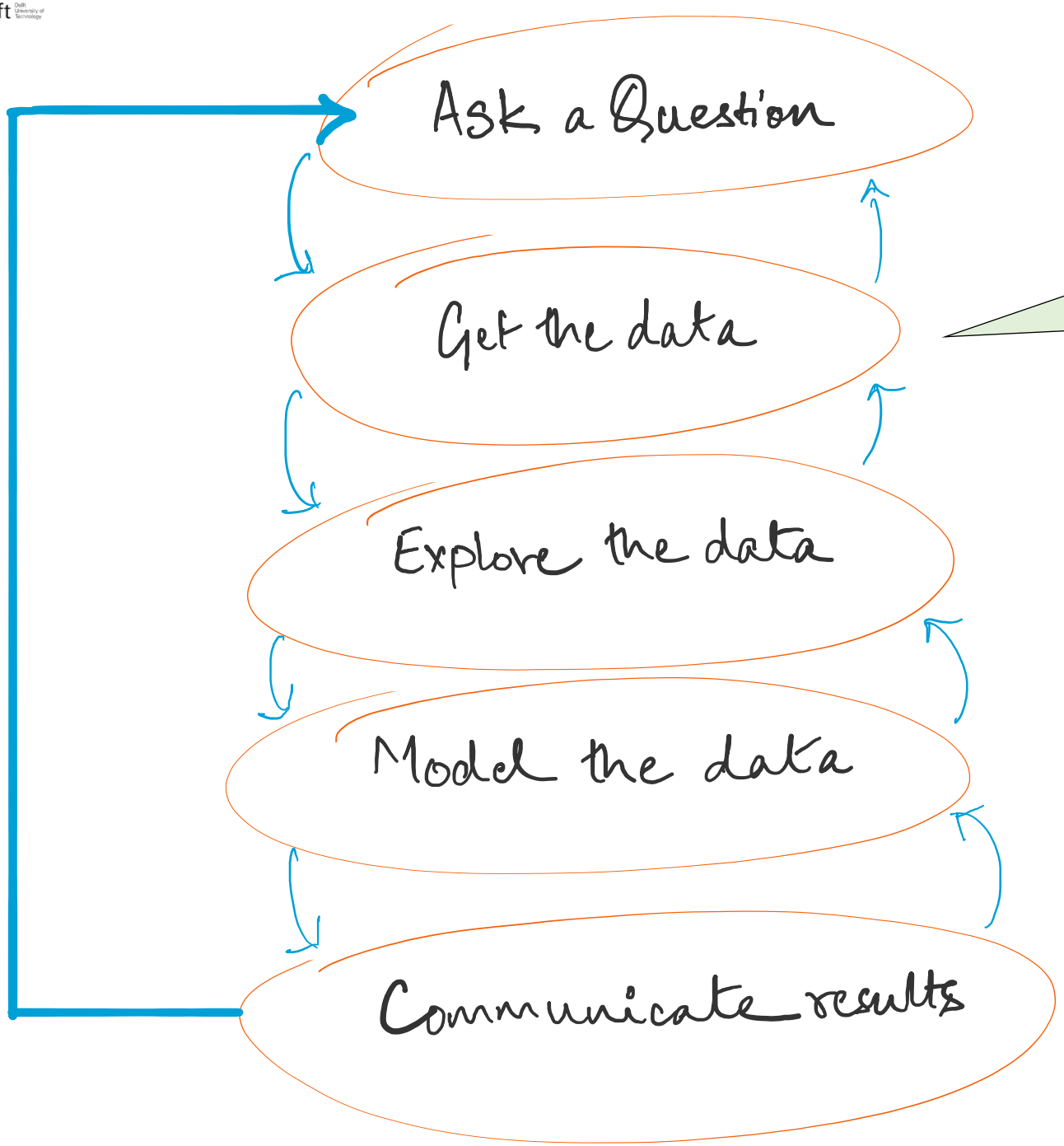


What is Data Science?

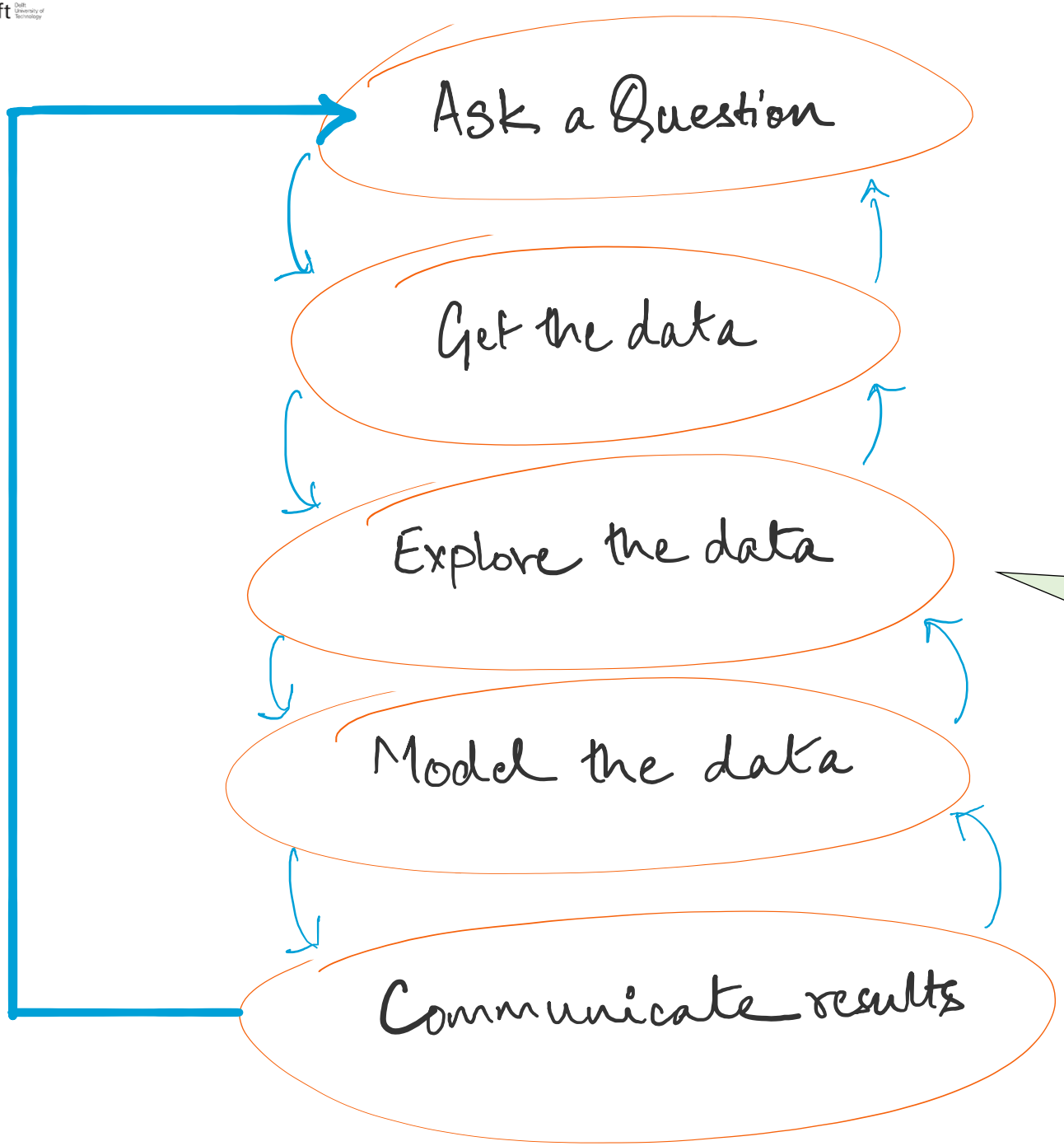

Ask a Question
Get the data
Explore the data
Model the data
Communicate results



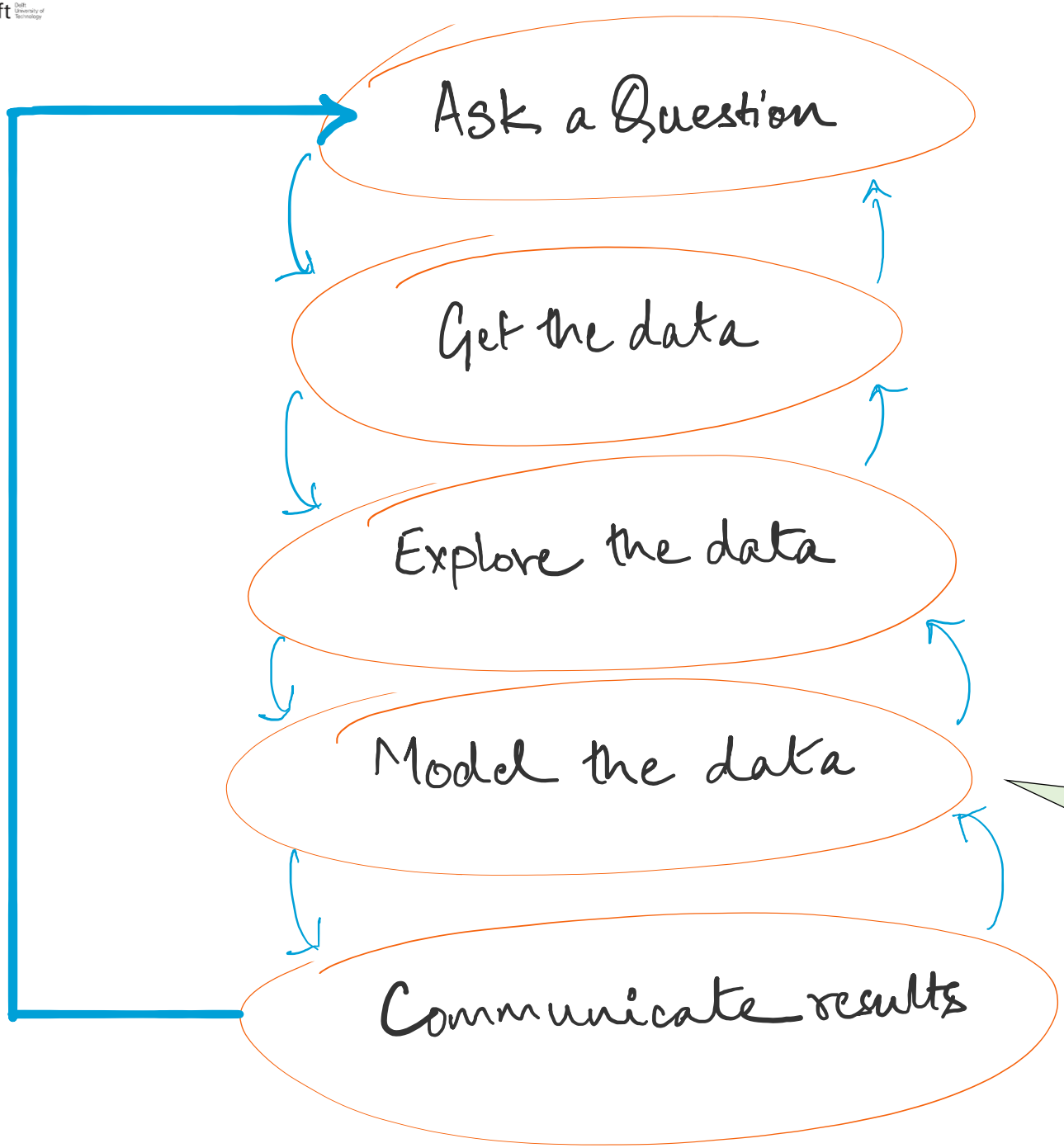
What is the scientific **goal**?
What would you do if you had all the **data**?
What do you want to **predict** or **estimate**?



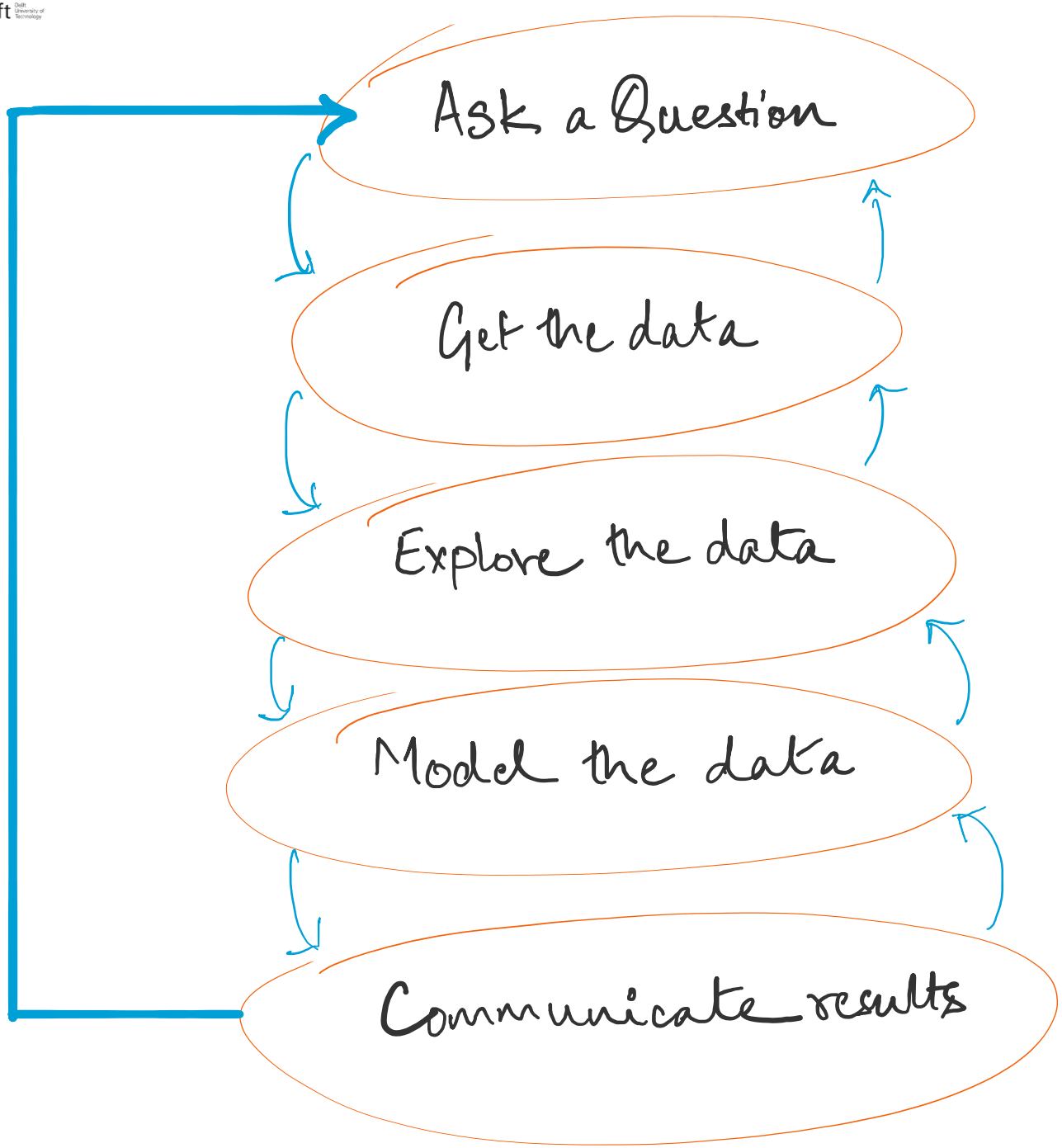
How were the data **sampled**?
Which data are **relevant**?
Are there **privacy** issues?



Plot the data.
Are there **anomalies**?
Are there **patterns**?

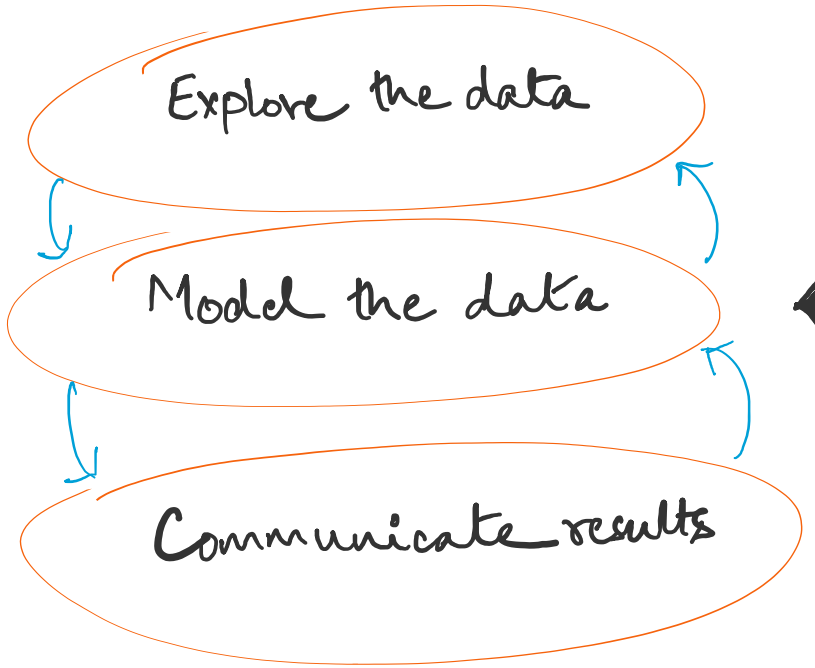


Build a model.
Fit the model.
Validate the model.



What did we **learn**?
Do the results make **sense**?
Can we tell a **story**?

EPA Programme



DATA

Agent based modelling — Igor Nikolic

Network Science — Piet van Mieghem

Machine Learning — CS Masters @ EWI

Survey methodology — TPM

System Dynamics — Willem Auping + Jan Kwakkel

Simulation — Alexander Verbraeck

DATA

Visualisation Q1

Uncertainty Jan Kwakkel Q4

What are we going to do?

The material of the course will integrate the five key facets of an investigation using data:

1. Obtain: Obtaining data from multiple open data sources.
2. Scrub: Data cleaning, *wrangling*, sampling to consolidate all information into a dataset that is manageable, informative and relates to your problem.
3. Explore: Exploratory data analysis to make sense of what your data is trying to say (build intuition).
4. Model: Estimation and modelling based on statistical tools such as regression and clustering.
5. Interpret: Communicating results and reflections through visualisation, storytelling and interpretable summaries.

The Data Science Process

The Data Science Process is like the scientific process - one of observation, model building, analysis and conclusion:

- Ask questions
- Data Collection
- Data Exploration
- Data Modeling
- Data Analysis
- Visualization and Presentation of Results

Note: This process is by no means linear!

Analysing Hubway Data

- **Introduction:** Hubway (now called BlueBikes) is metro-Boston's public bike share program, with more than 1600 bikes at 160+ stations across the Greater Boston area. Hubway is owned by four municipalities in the area.

- By 2016, Hubway operated 185 stations and 1750 bicycles, with 5 million rides since launching in 2011.

- **The Data:** In April 2017, Hubway held a Data Visualization Challenge at the Microsoft NERD Center in Cambridge, releasing 5 years of trip data.

- **The Question:** What does the data tell us about the ride share program?

The Data Exploration Cycle

Our original question: **'What does the data tell us about the ride share program?'** is a reasonable slogan to promote a hackathon. It is not good for guiding scientific investigation.

Before we can refine the question, we must look at the data!

	seq_id	hubway_id	status	duration	start_date	strt_statn	end_date	end_statn	bike_nr	subsc_type	zip_code	birth_date	gender
0	1	8	Closed	9	7/28/2011 10:12:00	23.0	7/28/2011 10:12:00	23.0	B00468	Registered	'97217	1976.0	Male
1	2	9	Closed	220	7/28/2011 10:21:00	23.0	7/28/2011 10:25:00	23.0	B00554	Registered	'02215	1966.0	Male
2	3	10	Closed	56	7/28/2011 10:33:00	23.0	7/28/2011 10:34:00	23.0	B00456	Registered	'02108	1943.0	Male
3	4	11	Closed	64	7/28/2011 10:35:00	23.0	7/28/2011 10:36:00	23.0	B00554	Registered	'02116	1981.0	Female
4	5	12	Closed	12	7/28/2011 10:37:00	23.0	7/28/2011 10:37:00	23.0	B00554	Registered	'97214	1983.0	Female

Based on the data, what kind of questions can we ask?

The Data Exploration Cycle

Who? Who's using the bikes?

Refine into specific hypotheses:

- More men or more women?
- Older or younger people?
- Subscribers or one-time users?

The Data Exploration Cycle

Where? Where are bikes being checked out?

Refine into specific hypotheses:

- More in Boston than Cambridge?
- More in commercial or residential?
- More around tourist attractions?

Sometimes the data is given to you in pieces and must be merged!

The Data Exploration Cycle

When? When are the bikes being checked out?

Refine into specific hypotheses:

- More during the weekend than on the weekdays?
- More during rush hour?
- More during the summer than the fall?

Sometimes the feature you want to explore doesn't exist in the data and must be engineered!

The Data Exploration Cycle

Why? For what reasons/activities are people checking out bikes?

Refine into specific hypotheses:

- More bikes are used for recreation than commute?
- More bikes are used for touristic purposes?
- Bikes are used to bypass traffic?

Do we have the data to answer these questions with reasonable certainty?

What data do we need to collect in order to answer these questions?

The Data Exploration Cycle

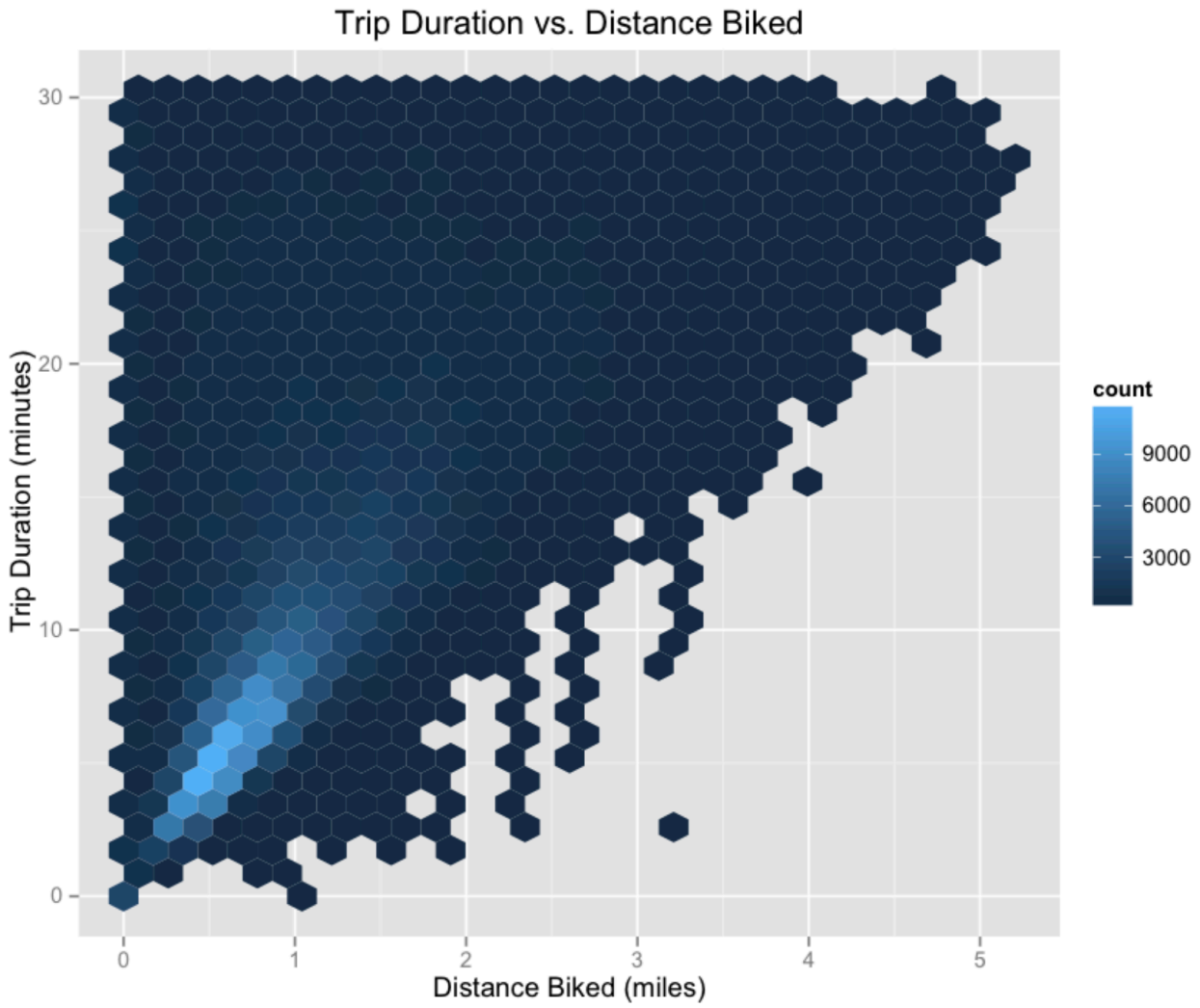
How? Questions that combine variables.

- How does user demographics impact the duration the bikes are being used? Or where they are being checked out?
- How does weather or traffic conditions impact bike usage?
- How do the characteristics of the station location affect the number of bikes being checked out?

How questions are about modeling relationships between different variables.

Inspiration for Exploring

So how well did we do in formulating creative hypotheses and manipulating the data for answers?



Break

WATER

WALK

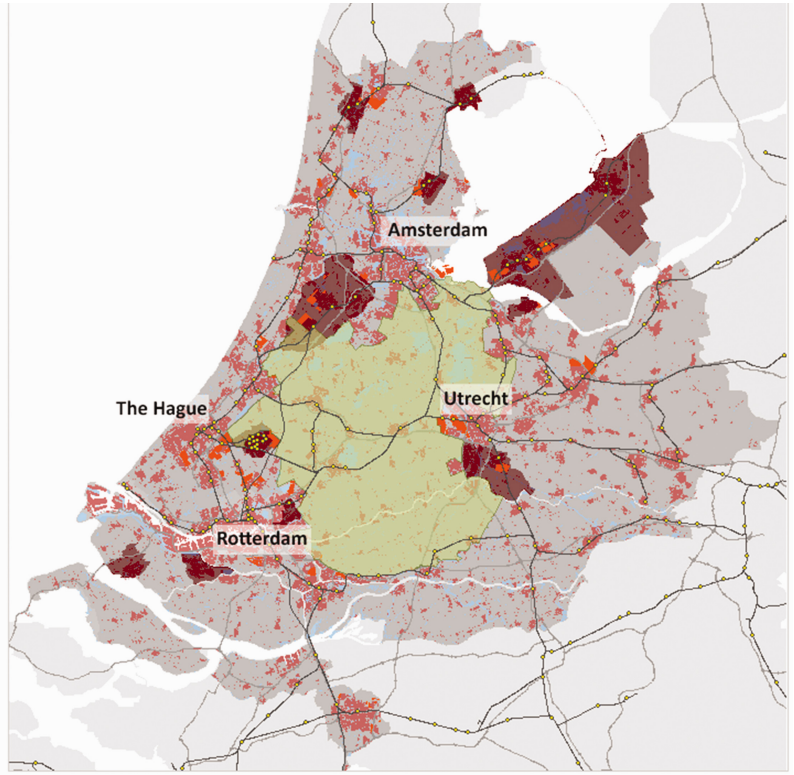
COFFEE OR TEA

MAKE FRIENDS

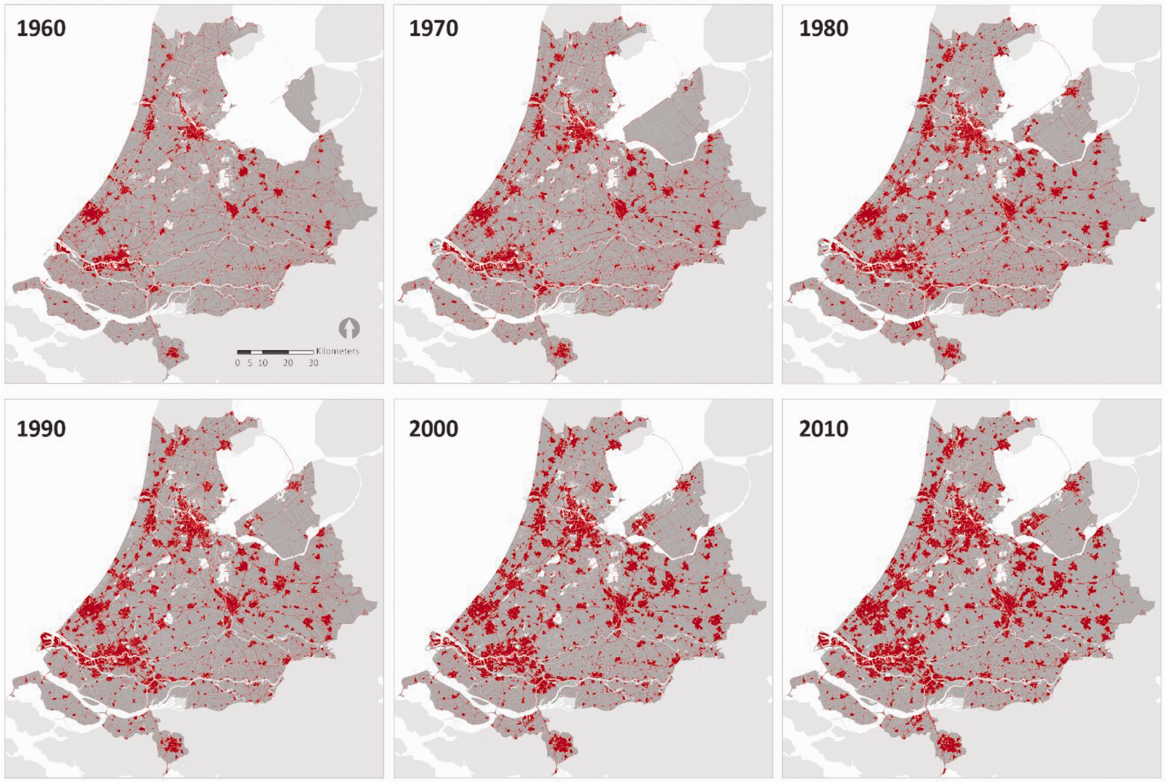
Role of Evidence in Policy

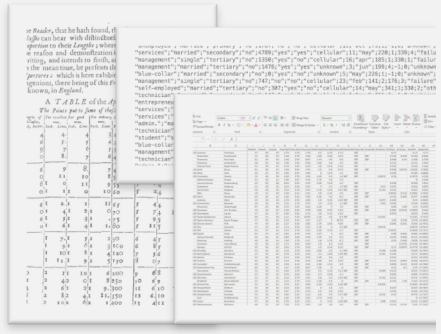
Kasraian, Dena, et al. "The impact of urban proximity, transport accessibility and policy on urban growth: A longitudinal analysis over five decades." *Environment and Planning B: Urban analytics and City Science* (2017)

Example: Randstad

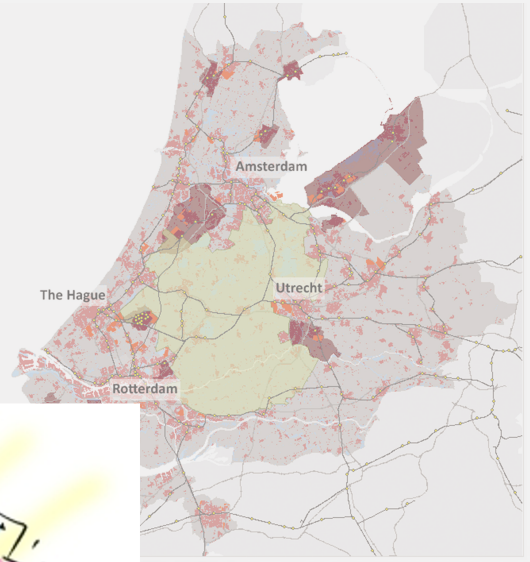


Urbanisation of the Greater Randstad Area 1960-2010





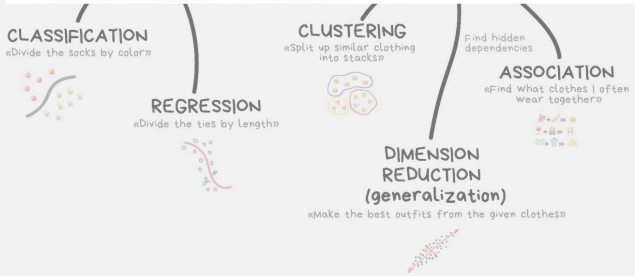

LET'S SOLVE THIS PROBLEM BY USING THE BIG DATA NONE OF US HAVE THE SLIGHTEST IDEA WHAT TO DO WITH

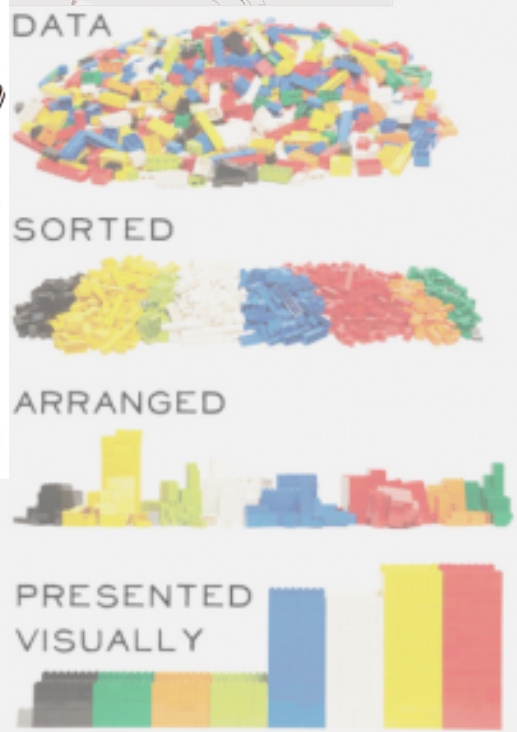

Amsterdam
The Hague
Utrecht
Rotterdam


A)
B)
C)
D)
Cases per Km²
RR
Bandwidth=100 m
Kernel = Epanechnikov
Bandwidth=700 m
Kernel = Quadratic
Bandwidth=100 m
Bandwidth=300 m
5 KM


? UM ?!!


Geographical
Cultural
Scientific
Financial
Statistical
Meteorological
Natural
Transport
Types of Data
?


CLASSIFICATION
«Divide the socks by color»
REGRESSION
«Divide the ties by length»
CLUSTERING
«Split up similar clothing into stacks»
Find hidden dependencies
DIMENSION REDUCTION (generalization)
«Make the best outfits from the given clothes»
ASSOCIATION
«Find what clothes I often wear together»


DATA
SORTED
ARRANGED
PRESENTED VISUALLY

Problem Understanding (Vision)

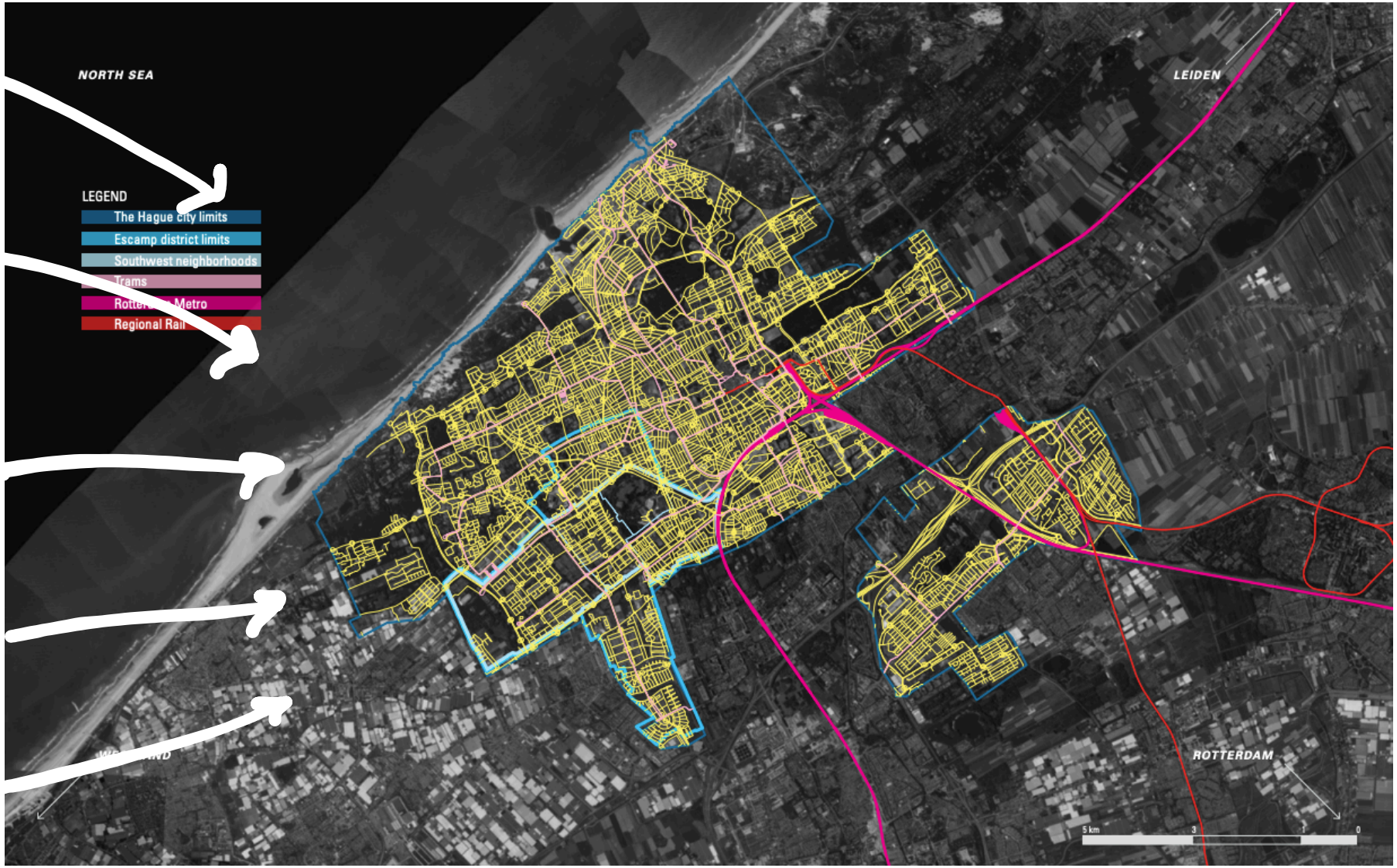
SUSTAINABLE

RESILIENT

INCLUSIVE

SMART

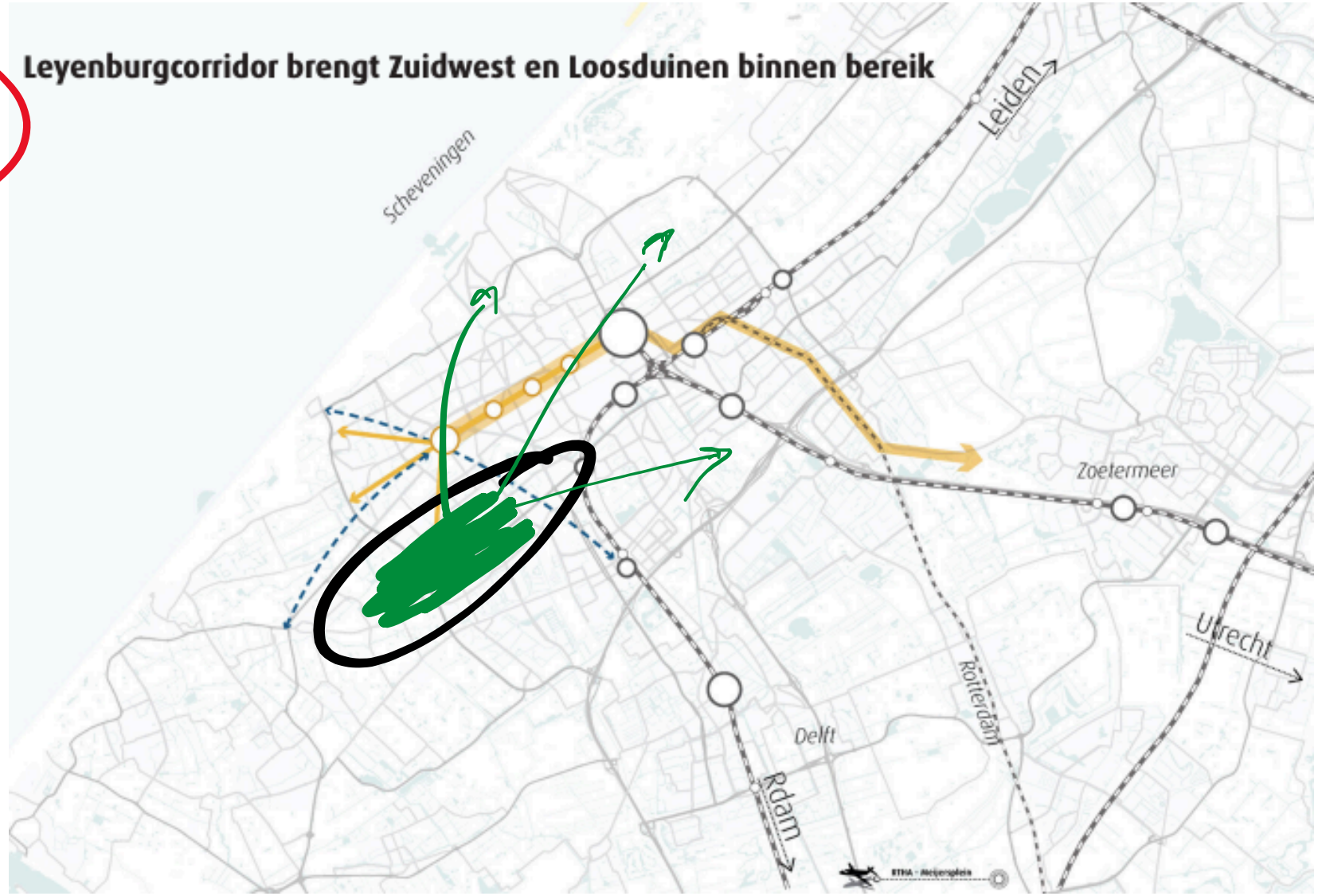
EQUITABLE



Problem Understanding

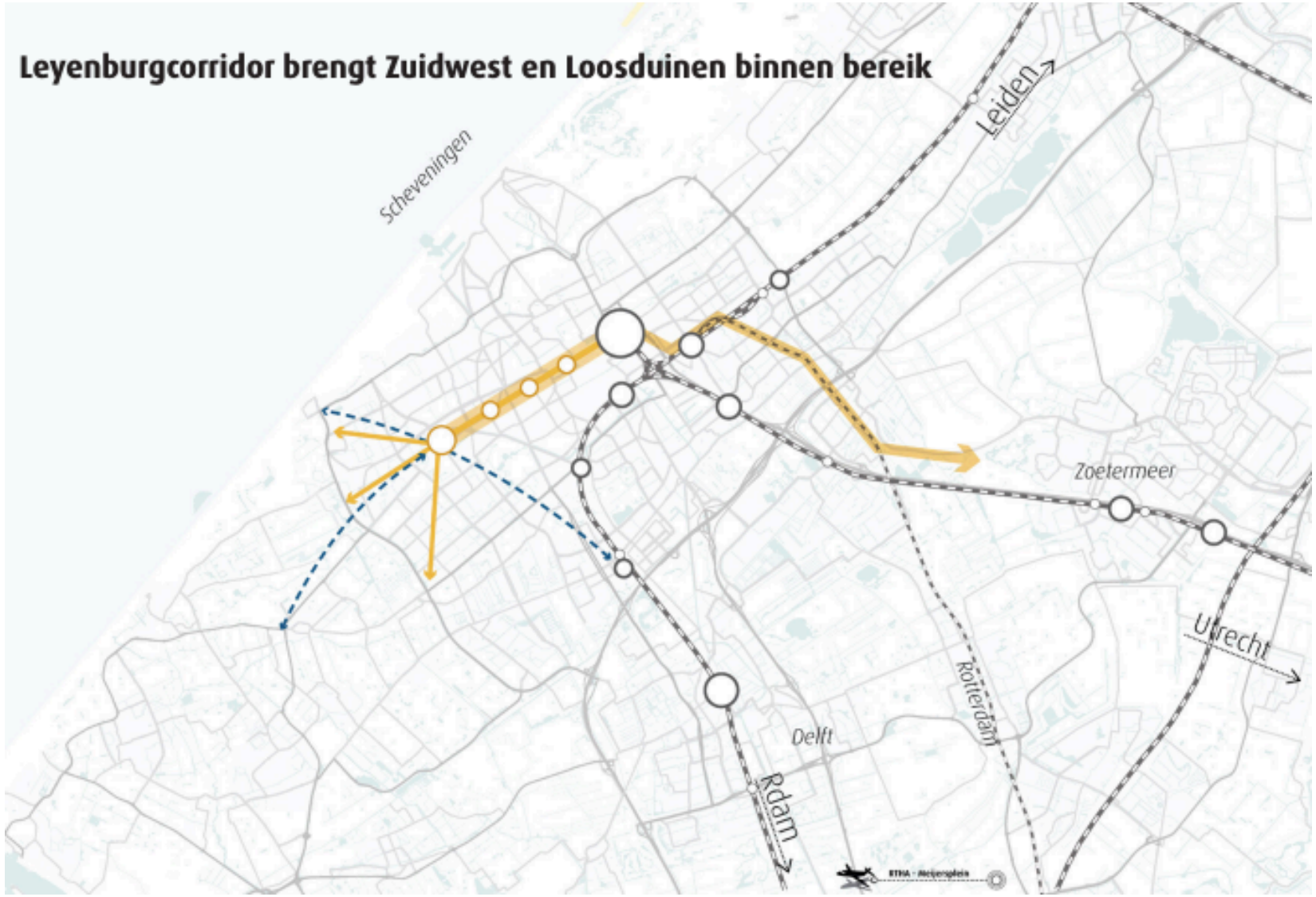
Poor Neighbourhood

Promote
- → Development
- → Social Cohesion
- → Access to jobs + infrastructure
- → Reduce car trips + increase PT use



Problem Understanding

- Determine what the objectives are
- Assess the situation
  resources, risks, costs and benefits
- Determine data mining goals
- Develop a project plan
  estimate timeline, budget, but also tools and techniques



Problem Understanding

- Difficult!
- Often, new knowledge required
- Explain limitations to non-experts
  - Do you have data? “No”
  - Accuracy will be 0.5%
  - Not next month, maybe next year

IN CS, IT CAN BE HARD TO EXPLAIN THE DIFFERENCE BETWEEN THE EASY AND THE VIRTUALLY IMPOSSIBLE.

Problem Understanding

My DOs and DON'TS

- Be extremely patient for vaguely defined problems
- Concretely reduce the scope of the idea
  - Data Samples are essential
  - Real-life case studies
  - Measures for success
- Ill-defined and unrealistic? Go to the beach

TED Talk

Cesar A. Hidalgo
@cesifoti

When you hear people define their academic field, among highly overlapping disciplines, the field names give you as much information about people's allegiance to a group, than about a set of concepts.

Learn to *look past* the keywords to basic *theory* and *concepts*

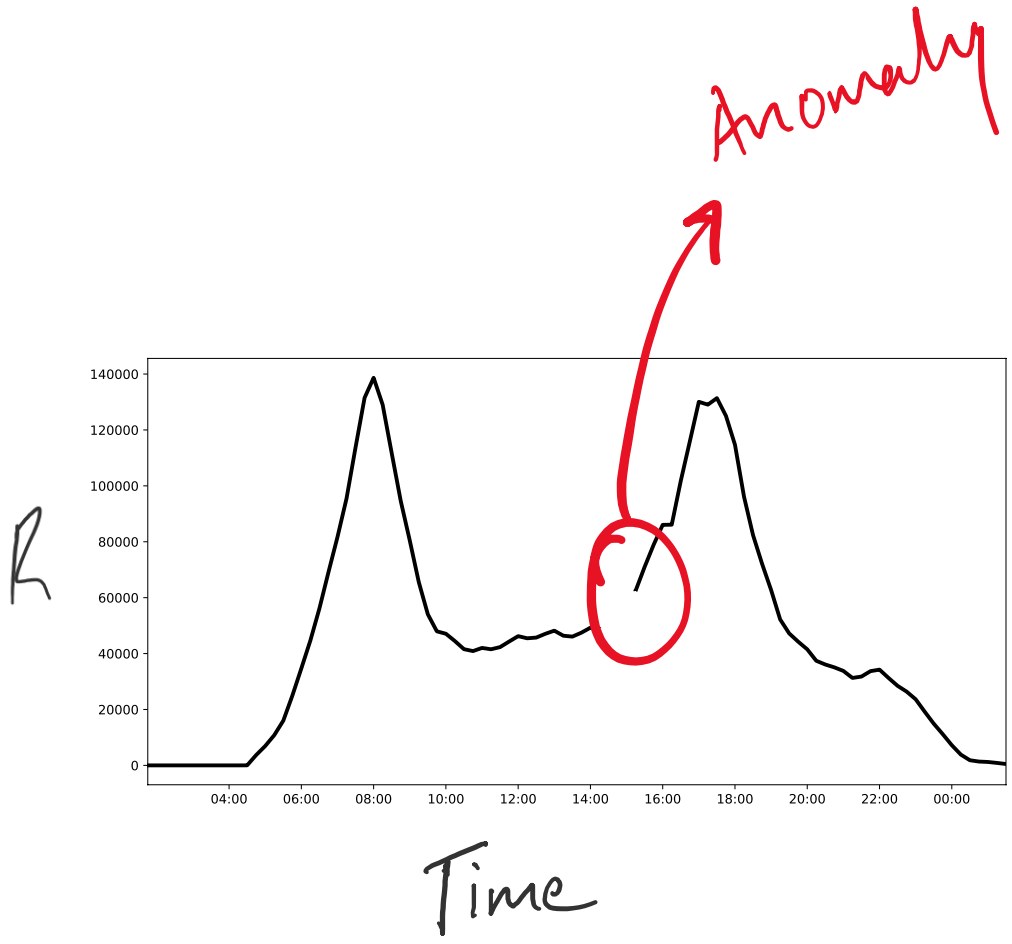
Ex. Design a sustainable food production system

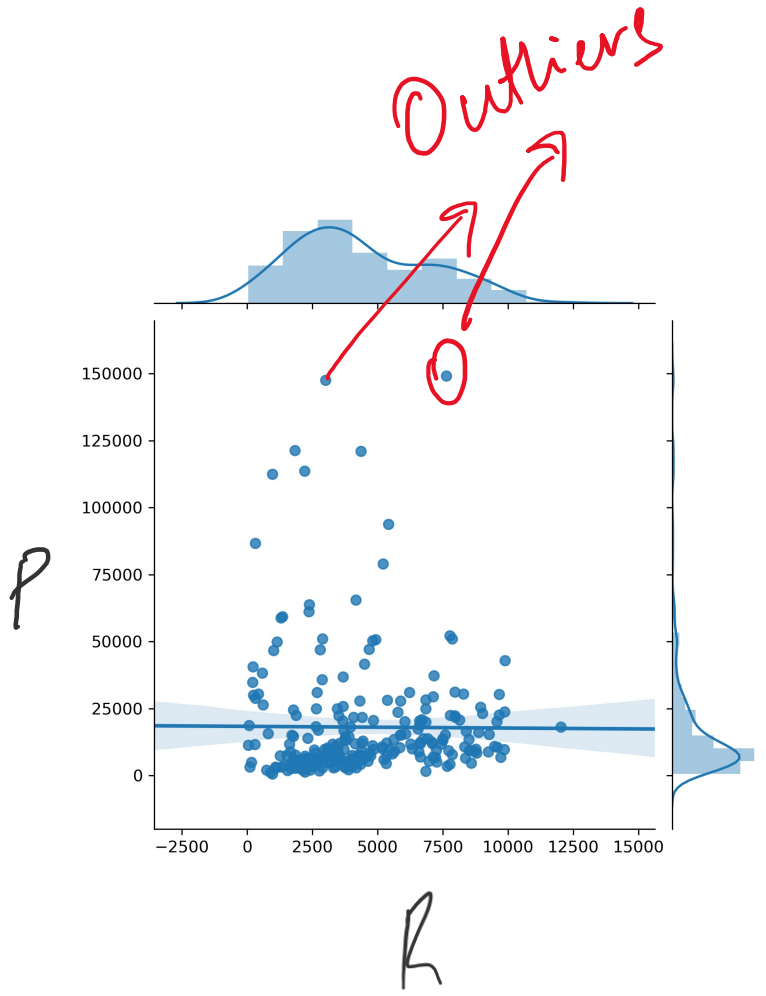
DS: What is a sustainable system?

Data Understanding & Preparation

Data Understanding

- Collect initial data
- Describe data
- Explore data
- Verify data quality
  carefully document problems and issues

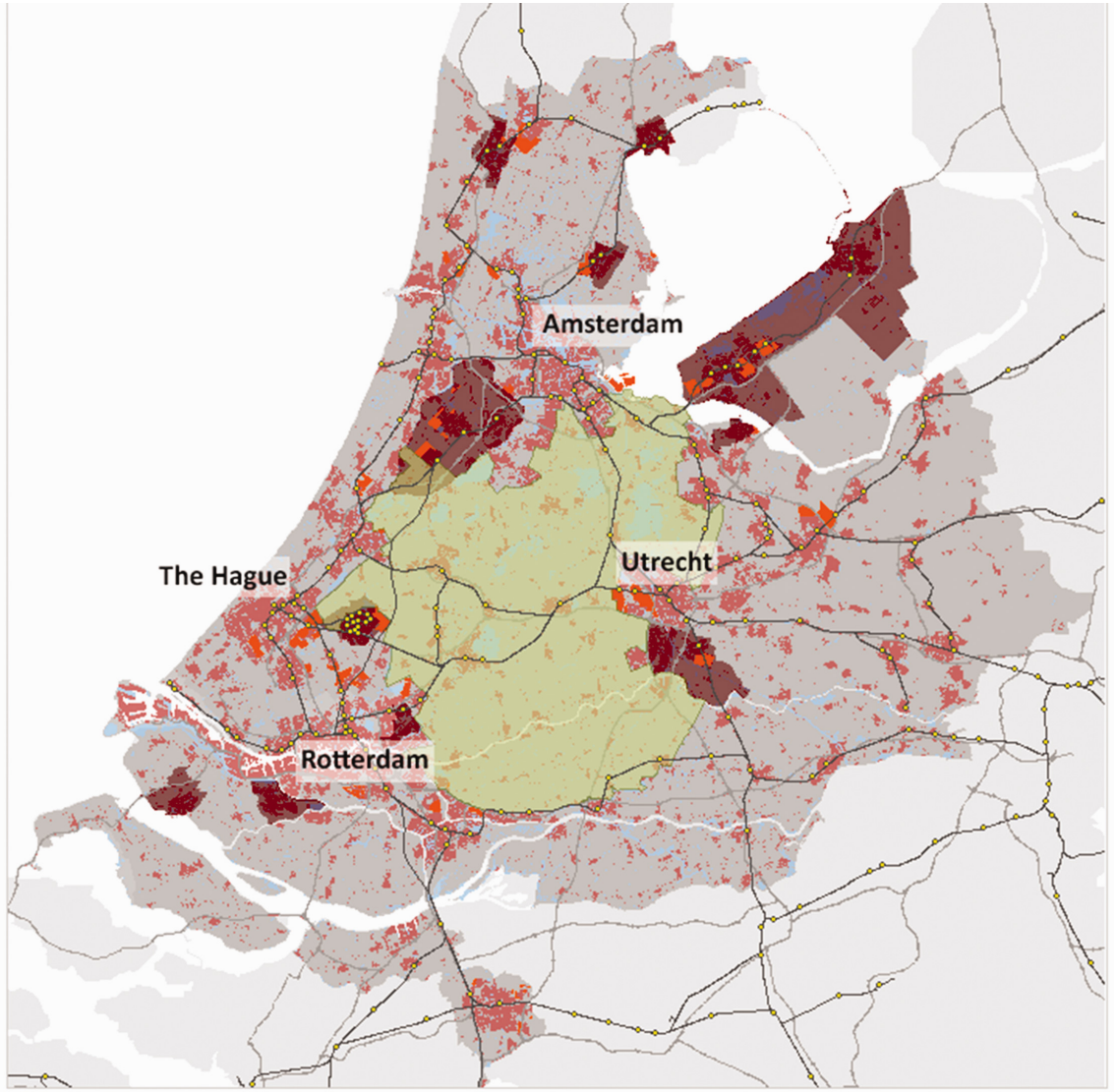




Data Understanding

My DOs and DON'TS

- Do not economise in this step
  - Data has issues
  - Understand data to understand the domain, very important for modelling later
- Do not trust the stakeholders supplying data for quality
- Verify data is **correct, complete, coherent, unique, representative, independent, up-to-date and stationary**
- Was the data processed? Anonymised? Still useful?
- Understand anomalies and outliers



Problem Understanding

Data Understanding

Data Preparation

Data Preparation

My DOs and DON'TS

- Automate this step as much as possible – new data / new case
- When merging sources, track data origin
- **Document everything!**
  Create a workflow
- Manage the stakeholders' expectations that these tasks will take roughly 50% of your time

Before you go for discussion..

Why do we use Functional programming

- **Organization** -- As programs grow in complexity, having all the code live inside the main() function becomes increasingly complicated. A function is almost like a mini-program that we can write separately from the main program, without having to think about the rest of the program while we write it. This allows us to reduce a complicated program into smaller, more manageable chunks, which reduces the overall complexity of our program.
- **Reusability** -- Once a function is written, it can be called multiple times from within the program. This avoids duplicated code ("Don't Repeat Yourself") and minimizes the probability of copy/paste errors. Functions can also be shared with other programs, reducing the amount of code that must be written from scratch (and retested) each time.
- **Testing** -- Because functions reduce code redundancy, there's less code to test in the first place. Also because functions are self-contained, once we've tested a function to ensure it works, we don't need to test it again unless we change it. This reduces the amount of code we must test at one time, making it much easier to find bugs (or avoid them in the first place).
- **Extensibility** -- When we need to extend our program to handle a case it didn't handle before; functions allow us to make the change in one place and have that change take effect every time the function is called.
- **Abstraction** -- In order to use a function, you only need to know its name, inputs, outputs, and where it lives. You don't need to know how it works, or what other code it's dependent upon to use it. This lowers the amount of knowledge required to use other people's code (including everything in the standard library).

For next class..

Finish Lab 01 to practice programming

Submit Homework 01 for peer review on Brightspace

Check Assignment 1 – due in **Week 2** on Friday at **2330**

See "To do before class" for every lecture (~ 1 hour of self study)

Read paper for **Discussion** session before every Friday

Post questions on the **Discussion** forum on Brightspace (especially on **Anaconda/Jupyter** section for this week)