# Data science: cases and observations

- ... from personal and Reaktor's point of view
  - Janne Sinkkonen

Our company, shortly

Doing data science in practice, from Reaktor's point of view And some opinions about things

A case example: Yle recommendations

More case examples if you wish (haven't prepared these but I have slides)

## Outline

We have plenty of time, and having some discussion is more entertaining and clarifying.

Chat (txt) or interrupt

### Please ask

### Offices mainly in Helsinki, but also NY, Stockholm, Amsterdam, Dubai, and a bit elsewhere (Tokyo, Tampere etc.)

Reaktor

R

100%

(past-)employee ownership

turnover 2020, est.

Reaktor strategic partners

**Reaktor Ventures & Reaktor partners** 

12

companies

R **REAKTOR** – CONFIDENTIAL 110M€

2000

Year founded

500 - 600

emloyees

24

startups

>15

countries



people





- 20 years, data science 8 years
- Growing maybe 10–20% per year, now also abroad
- Flat organization
- "Owned by employees", strong culture
- Emphasis on the human side: team, communication, wellbeing, ...
- Pioneer on agile methods; fits well with ds (empirical, iterative attitude)

### Reaktor: less formal

# **Consultancy vs. products**

Consultancy here means selling your work to customers who "own the product". You are in the role of an expert, but it's still mostly development, not slides!

Consultancy: technologically wide Products: technologically deep

You need some domain knowledge. Context, as opposed to the tech. core, is emphasised in practice. (Still you can't do it without understanding the technology.)

You are not in customer's organization, which is both good and bad.

# Reaktor data science etc.

Includes: data science, machine learning, "Al", data engineering

machine vision.

We work mostly in teams, from two to several people.

years.

- We don't have definite roles, so it is hard to say how many we are, but roughly 20-35.
- Not homogeneous: data engineering, statistics, sales, biz design, machine learning, NLP,

- Projects are pretty organic, often start with small and the grow up. Some last weeks, some



# AI, ML, ds

- All is a recent hype term (since  $\approx 2015$ ), harmful to markets.
- Used to mean almost human-level intelligence.
- Now wide in scope, includes linear regression in an operational context.

Data science is a cloudy concept as well.

- A useful division maybe, in practice:
- Inferential work, ≈ statistics, data science
- Operational systems, ≈ machine learning
- Infrastructure, cloud etc.,  $\approx$  data engineering
- Conceptual work around the core and before, ≈ Al/biz design



## Beware of data

Data is a useful term when it refers to storage or transfer. - In storage and transfer, semantics of bits mostly don't matter.

When data refers to **measurements** supposed to be operational or increase understanding, context is fundamental!

You need to understand in detail where the data originates.

Preferably, you should decide how it originates.

Compare to science: observational data vs. controlled experiments.

Report? Ok... where does it lead? What are the decisions, actions? - You need to know (estimate) the effects of those actions.

Operational system? It needs to act as well, i.e., make choices. - Again, you need causal inference (often implicit).

How can you know the effects of the actions without doing the actions? - Theory? Usually it is weak or nonexistent on many domains (sales, recommendations) - Or, you need actions/interventions, and this contradicts the idea of passive data.

You need controlled, experiments, reinforcement learning, etc.

# Data and then what?

### R Cornerstones of an "Al" solution

### ML / DS

- Design of measurements and interventions
- Integrity of data
- Models
- Interfaces of models (APIs)
- Implementation: efficiency, scalability etc.

### Data engineering

- Infrastructure
- Data flow, storage
- Security
- Transparency
- Correctness

### Biz design

- The goal: what it fulfills
- Possible?
- Who does it?
- Who needs to be involved at the customer
- "Operationalization"
  - Design of measurements (data) and interventions
  - Overall system architecture

# **Example: Yle recommendations**

- Yle: Finnish national newsmedia (compare to BBC, or NRK in Norway) Was: Radio and then TV Now: <u>yle.fi</u> and Areena, a Netflix-like streaming service
- Both the news web site and Areena need a recommendation system
- We have been doing this for about 6-7 years now.
- It is not all about a core algorithm. ;)

# Example of "data"

Data is a byproduct of Ul's, no-one has ever used it -> broken by default Heterogeneity of Uls (clients), with legacy: heterogeneity of data Heterogeneity of users: bots are involved, but no clearly separated "Item has been viewed": no clear definition

Non-causal: co-occurrences A&B, but do they imply A -> B or B -> A or both?

# Yle: environment

- Use of the service is preferred to non-use (reading time, viewing time, click rate)
- Yle wants to have young customers as well
- Yle also has somewhat lofty goals of education etc.
- Journalists, editors, they want to have a say -> hybrid system (ML & human)
- Huge long tail of content, popular content changing rapidly
- Diverse client software (including Elisa etc., Apple, etc.)

# Algorithmic solutions

Components, iterative development, lots of trial and error.

A/B testing? Yeah, but a long story.

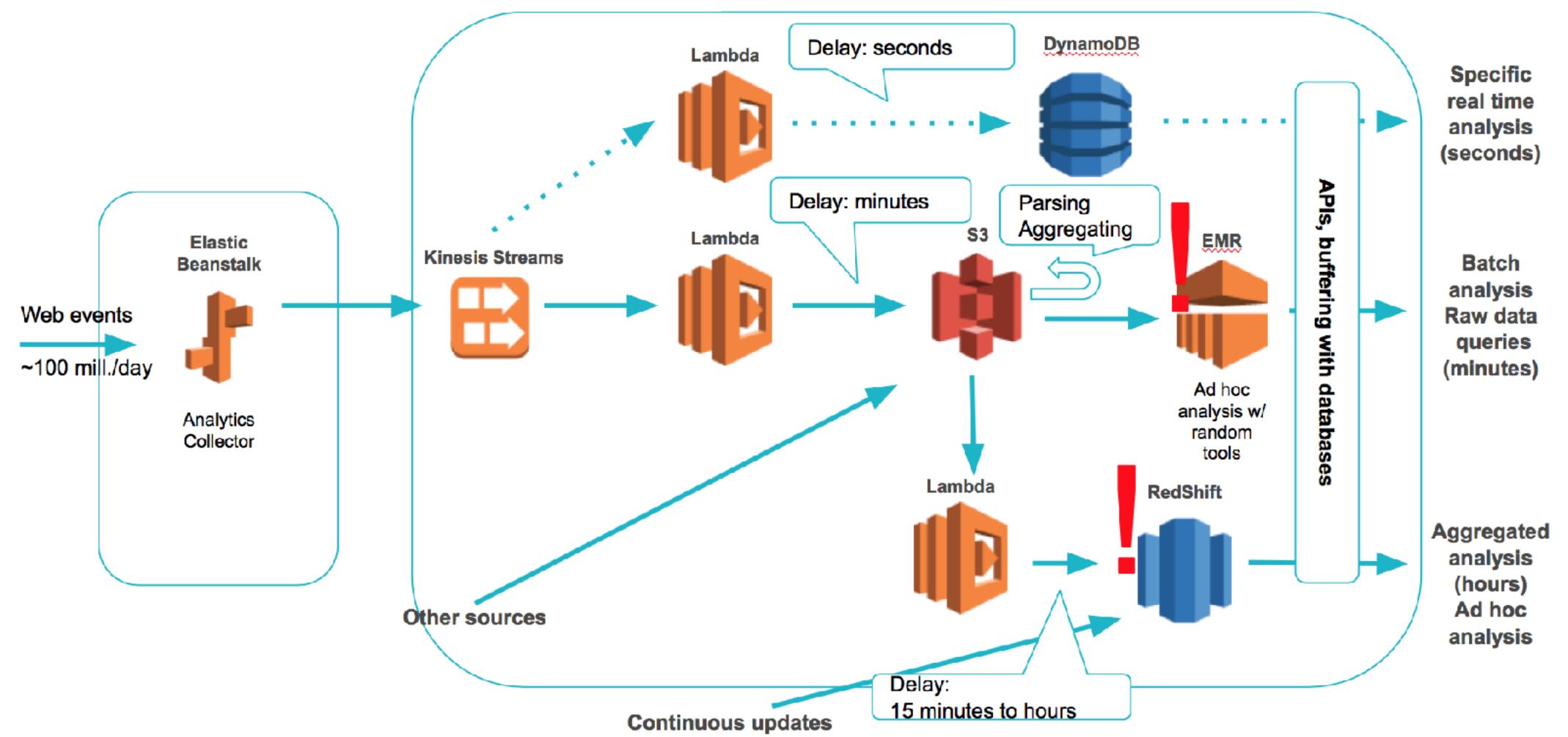
Matrix factorisation: good for genres etc.

Association rule -like heuristics: good for long tail, kind of local over content and users

Popularity separately

Some NLP



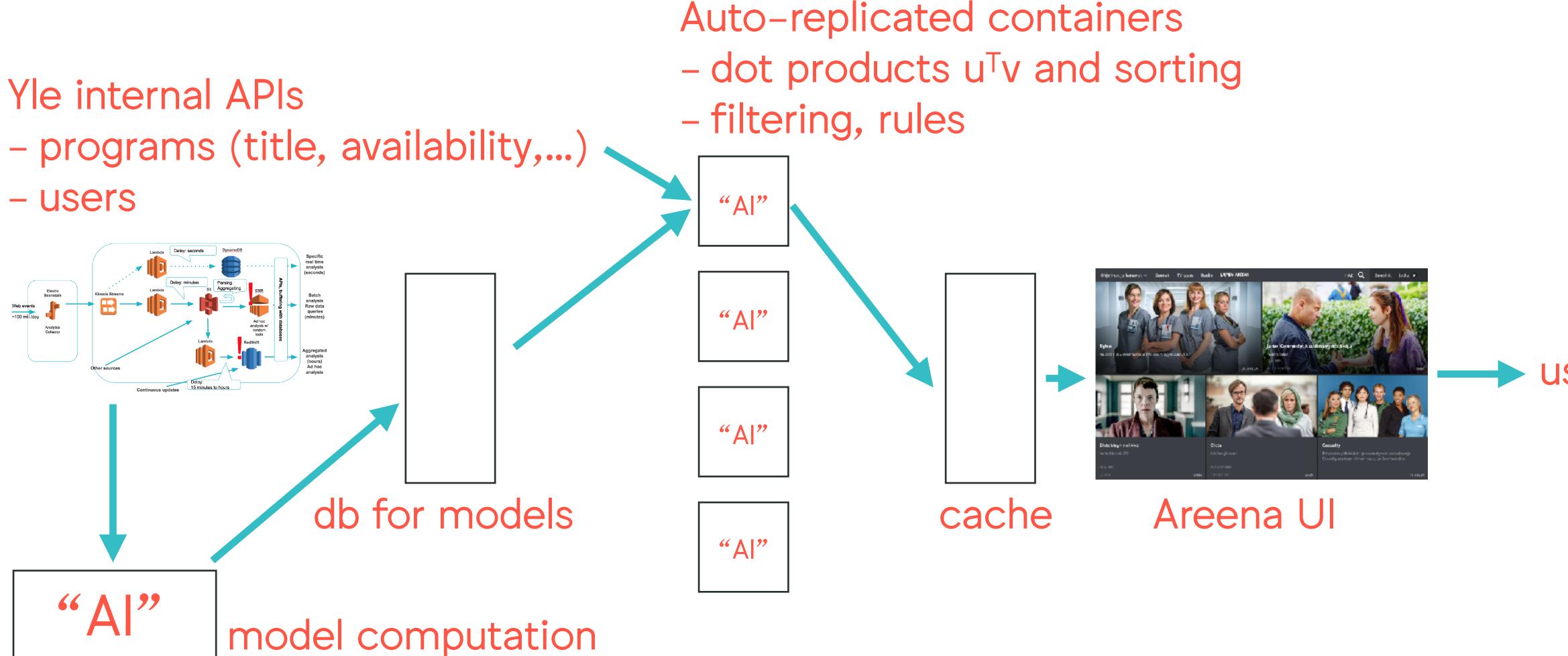


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### yle

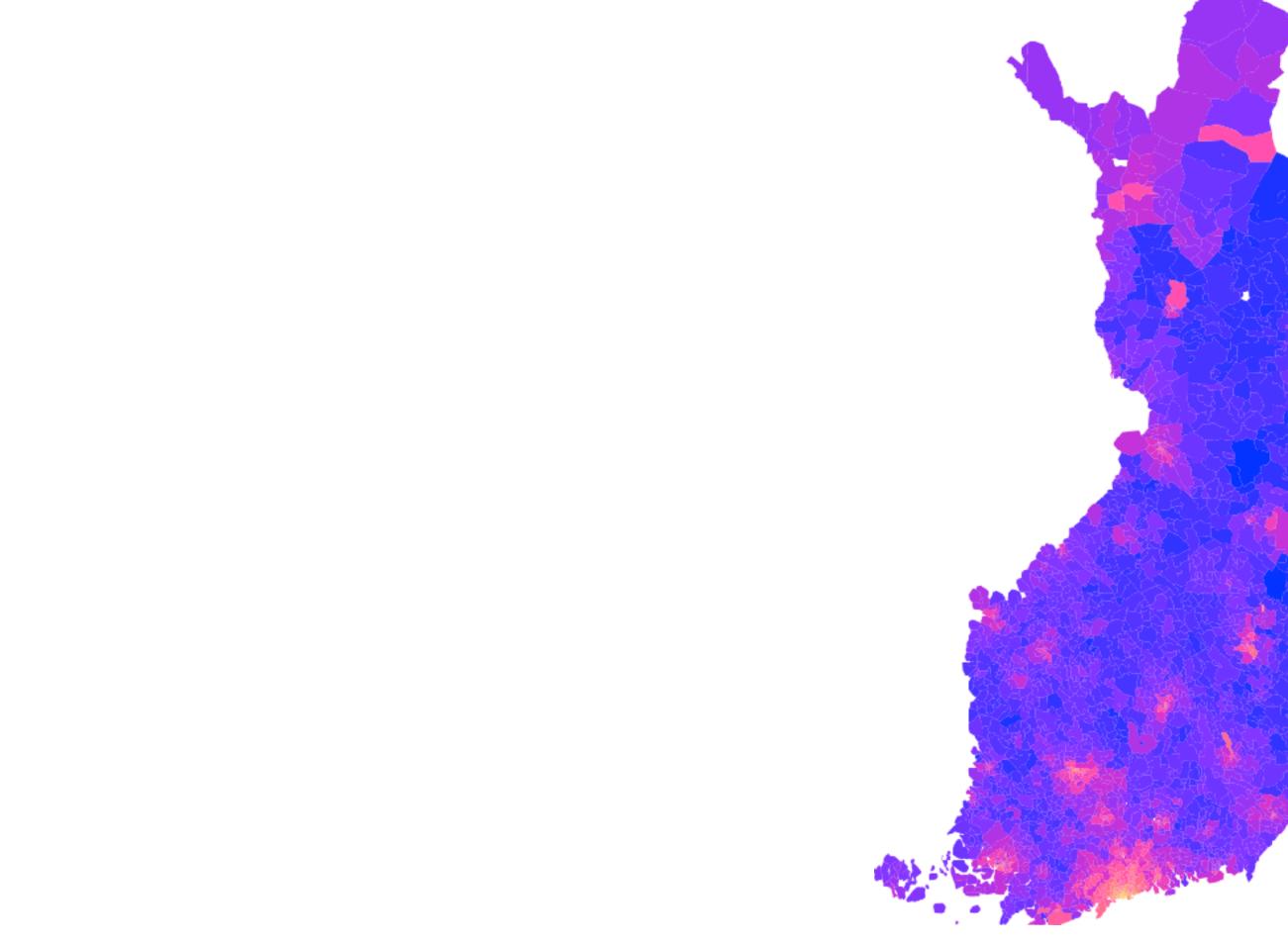


### Immediate architecture of recommendation





### Estate price level estimation



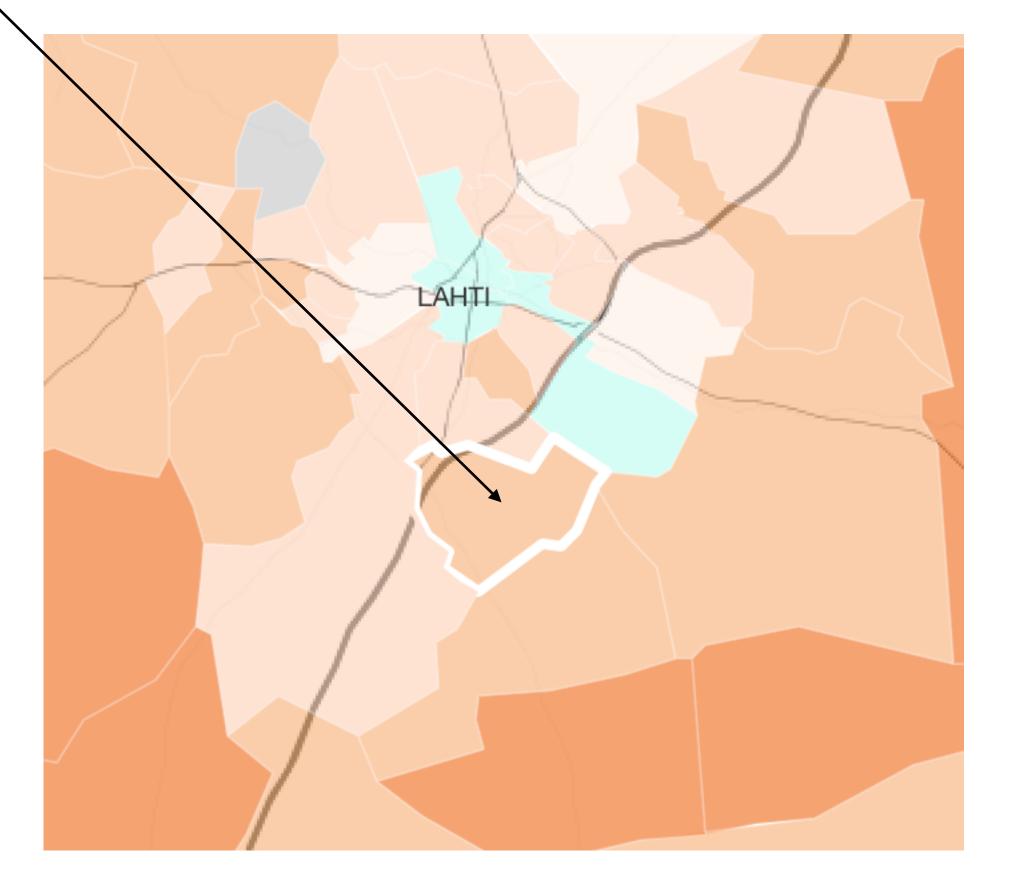
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### Estate price level estimation



<b>Renkomäki-Ämmälä</b> 15680 Lahti	$\times$	
Price per square meter per year 2005—2017		
2005 2010 2015		
1,500 -		$\mathbf{i}$

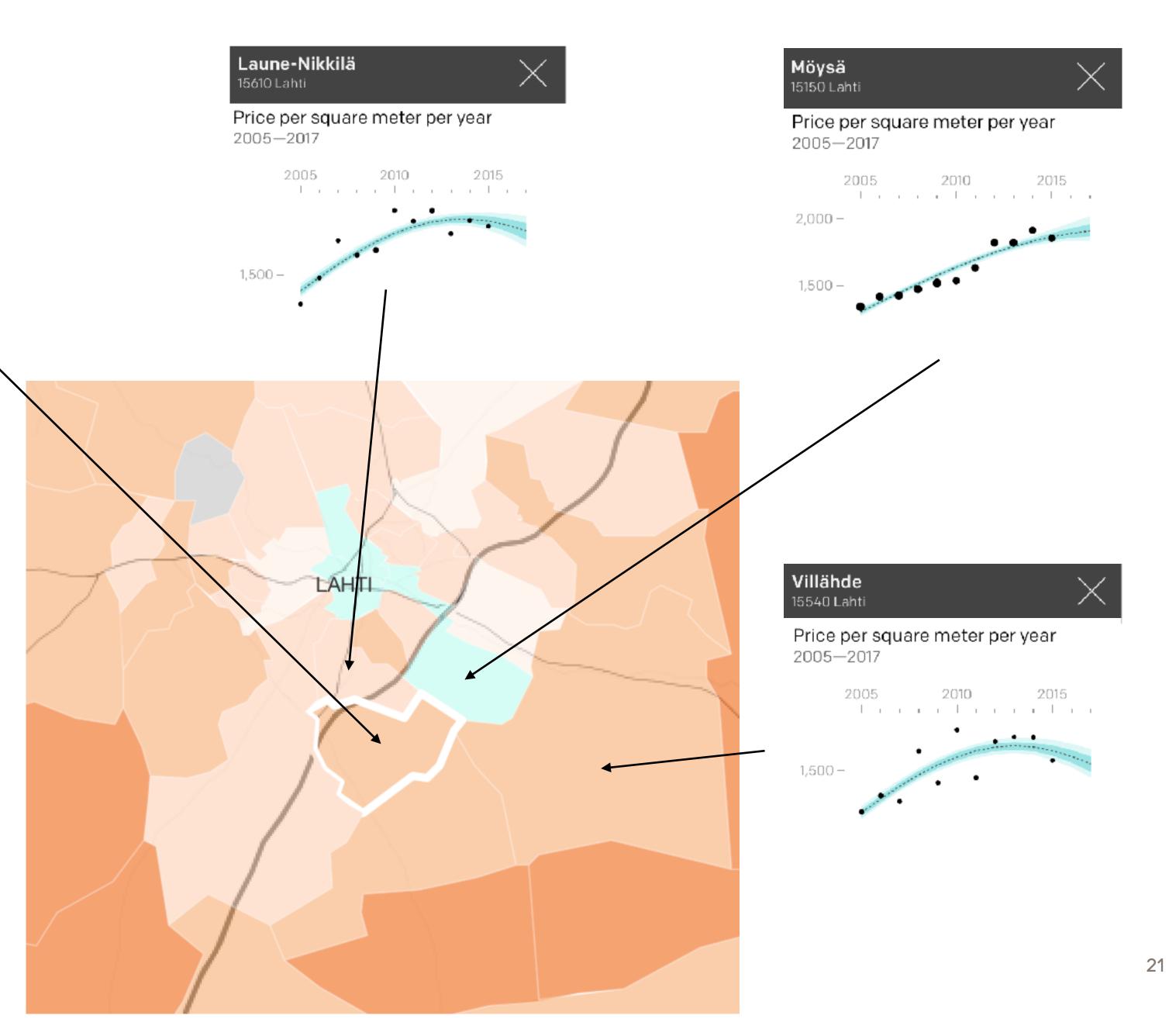
How to estimate the yearly prices for Renkomäki-Ämmälä?



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How to estimate the yearly prices for Renkomäki-Ämmälä?

Could borrow information from the adjacent ZIP codes.

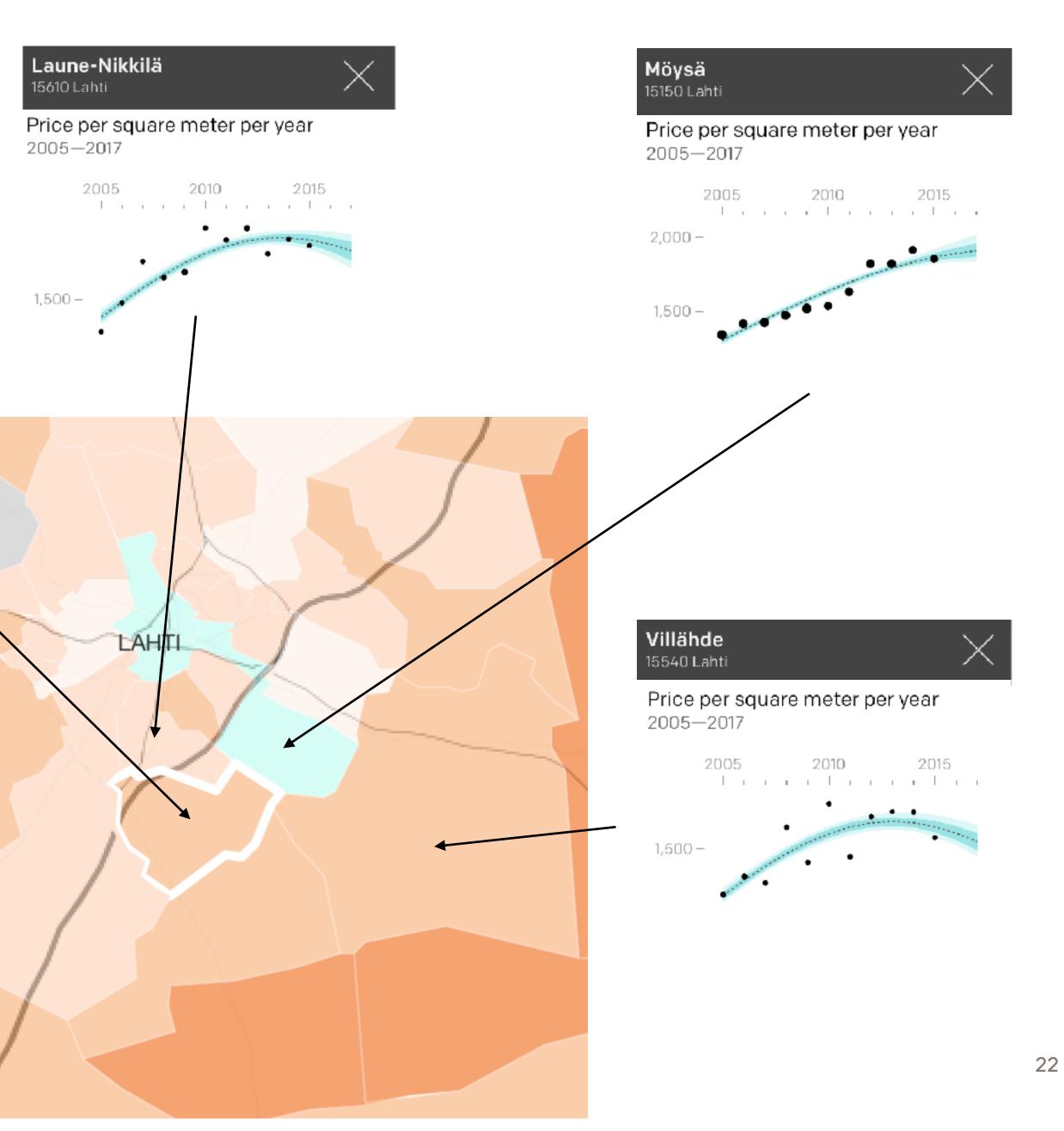


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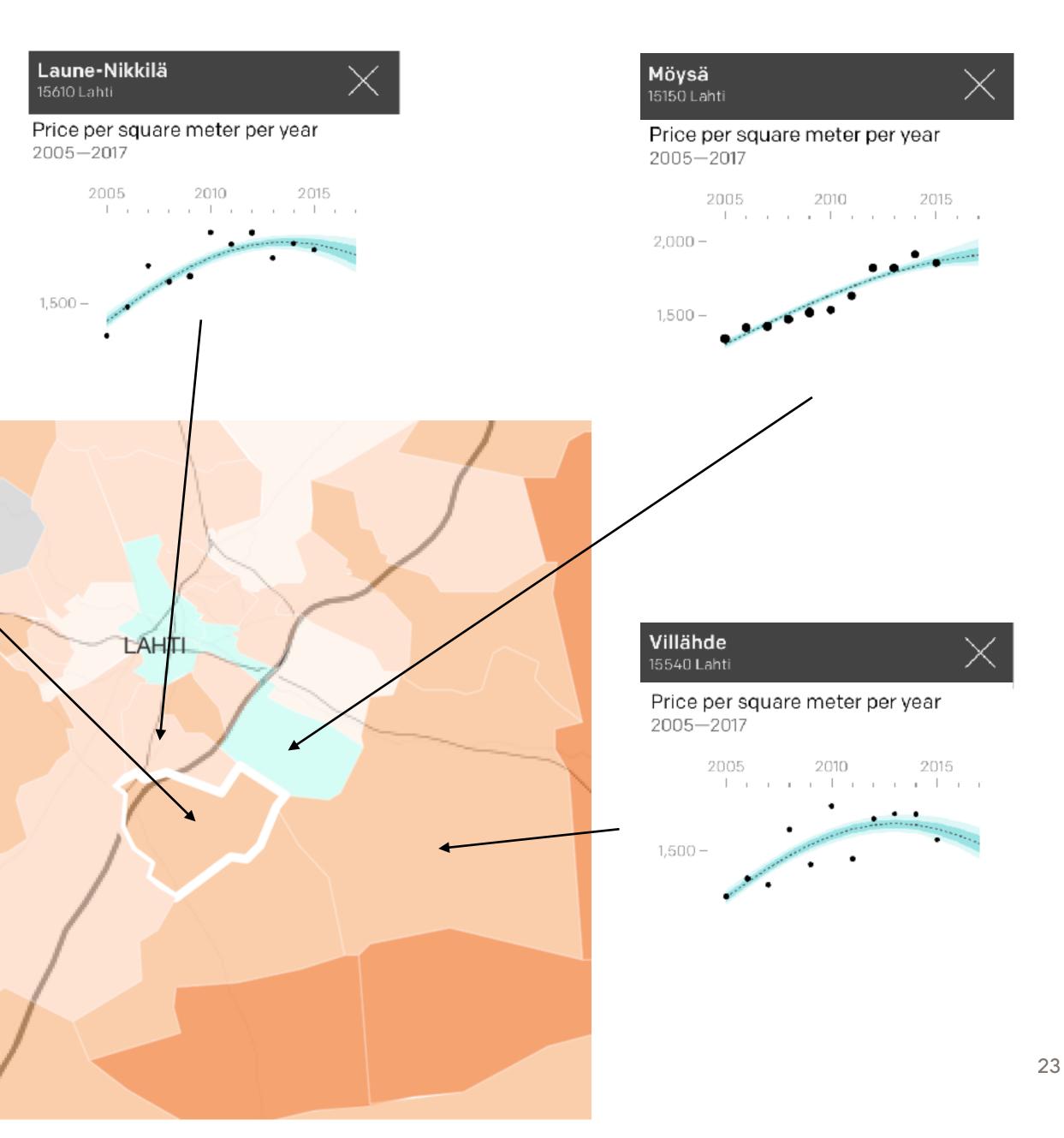
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But how to choose from contradicting information (e.g. increasing prices in Möysä, and decreasing prices in Laune-Nikkilä)?

Solution: use additional information (population density) about the similarity of the ZIP codes.



### The model

Use a quadratic model for time.

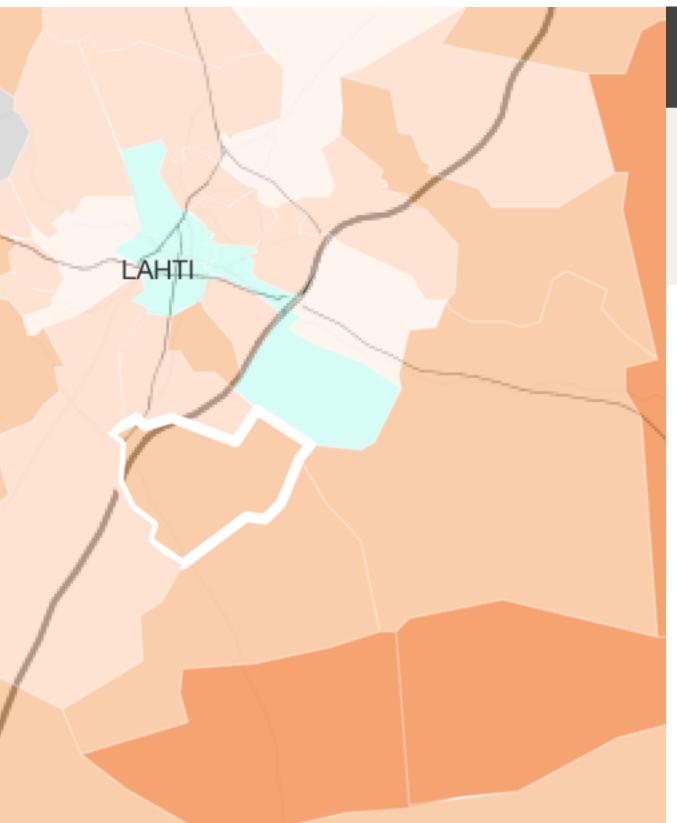
Use three levels of hierarchies for the postal code:

- 15680 (Renkomäki-Ämmälä)
- 156XX (Renkomäki-Ämmälä, Laune-Nikkilä)
- 15XXX (Renkomäki-Ämmälä, Laune-Nikkilä, Lahti, ...)

Use the population density of the 156XX.

The model on the lowest level of hierarchy:

$$\log h_{it} = \beta_{i1} + \beta_{i2}t + \beta_{i3}t^2 + \beta_{i'4}d_i + \beta_{i'5}d_it + \beta_{i'6}d_it^2,$$
$$\log y_{it} \sim t \left(\log h_{it}, \sqrt{\sigma_y^2 + \frac{\sigma_w^2}{n_{it}}}, \nu\right),$$



### Renkomäki-Ämmälä 15680 Lahti

population: 3,229 avg. price 2017: 1,559 € per m<sup>2</sup> trend 2017: -3.29 % per year

### Price per square meter per year 2005–2017

