

# Modeling, Measuring and Exploiting Concept Drift in the Labour Market Domain

*Panos Alexopoulos & Spyretta Leivaditi*

*2nd Drift-a-LOD Workshop,*

*Amsterdam, Netherlands, September 11th 2017*

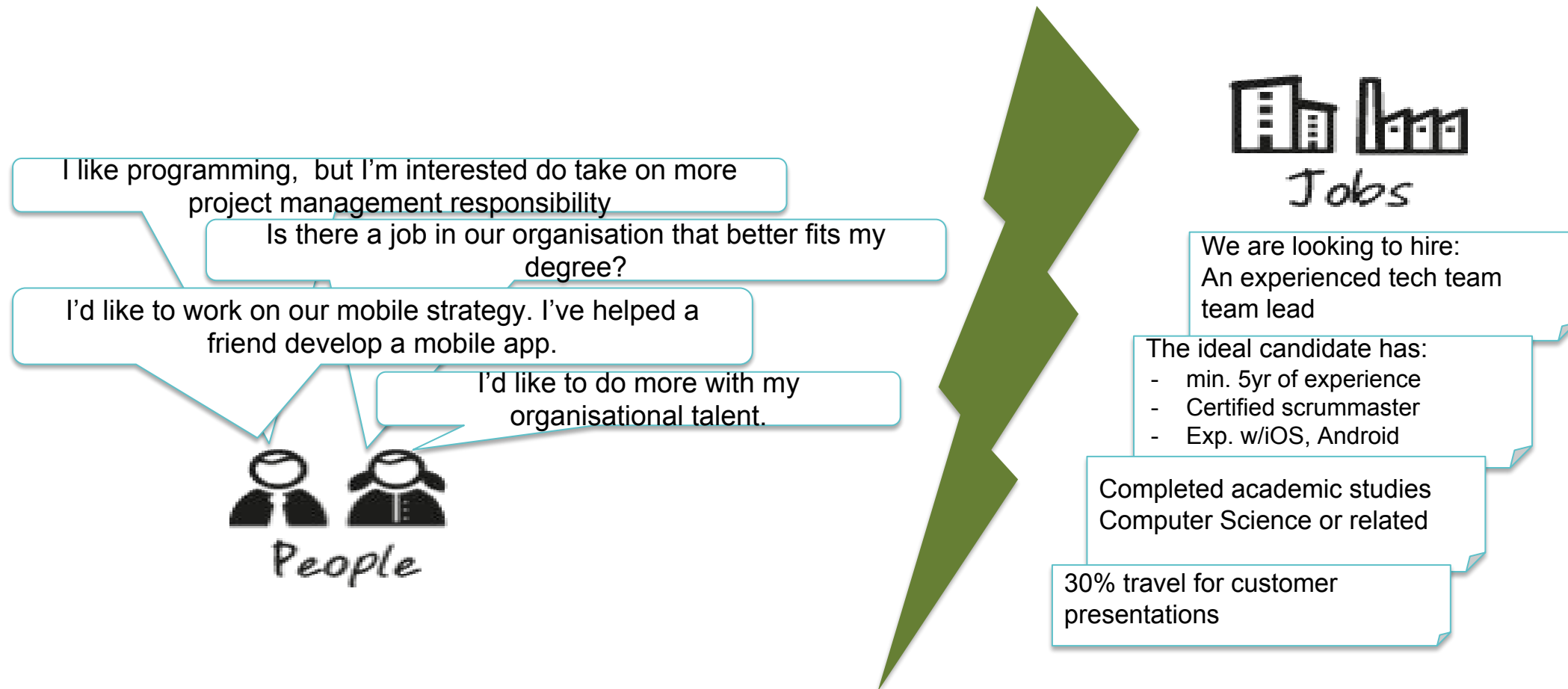


**textkernel**

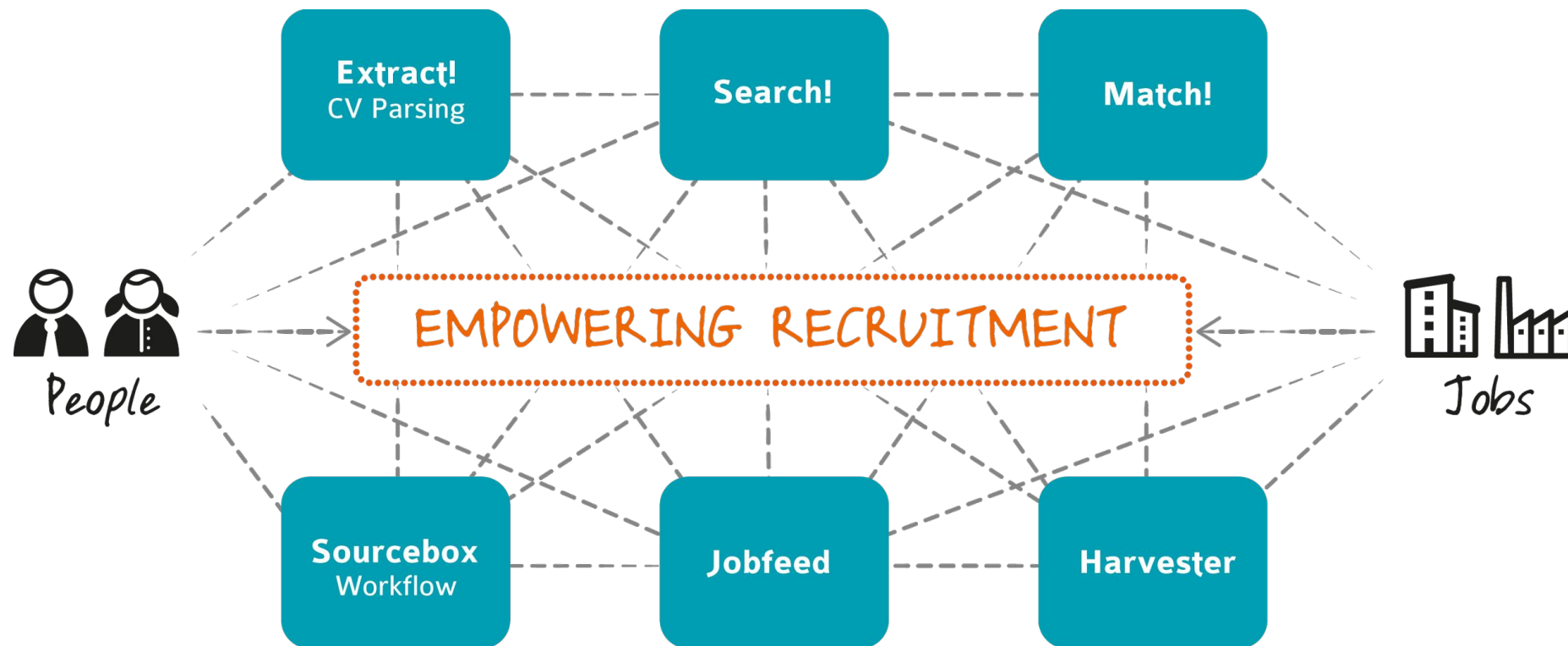
Machine Intelligence for People and Jobs

Who we are and  
what we do

# We develop Technology to bridge the language and meaning gap between People and Jobs ...



... through a family of sophisticated software products ...



... that large organizations in the HR and Recruitment sector use...



# Our Knowledge Graph

# Schema Overview

- **Concept Types:**
  - Professions
  - Skills
  - Qualifications (Degrees, Certificates)
  - Organizations (Companies, Educational Institutes)
  - Industries
- **General relations:**
  - prefLabel and altLabel
  - broader and narrower

# Domain-Specific Relations

- **Professions are linked to:**
  - Skills and activities they involve
  - Locations, organizations and industries where they are found.
  - Qualifications that are (formally or informally) required for their exercise
  - Similar professions
- **Skills are linked to:**
  - Similar skills and activities,
  - Professions and industries they are mostly demanded by
  - Qualifications that develop and verify them.
- **Qualifications are linked to:**
  - Skills that have as learning outcomes
  - Organizations that provide them
  - The educational levels they cover.



# Relation Vagueness

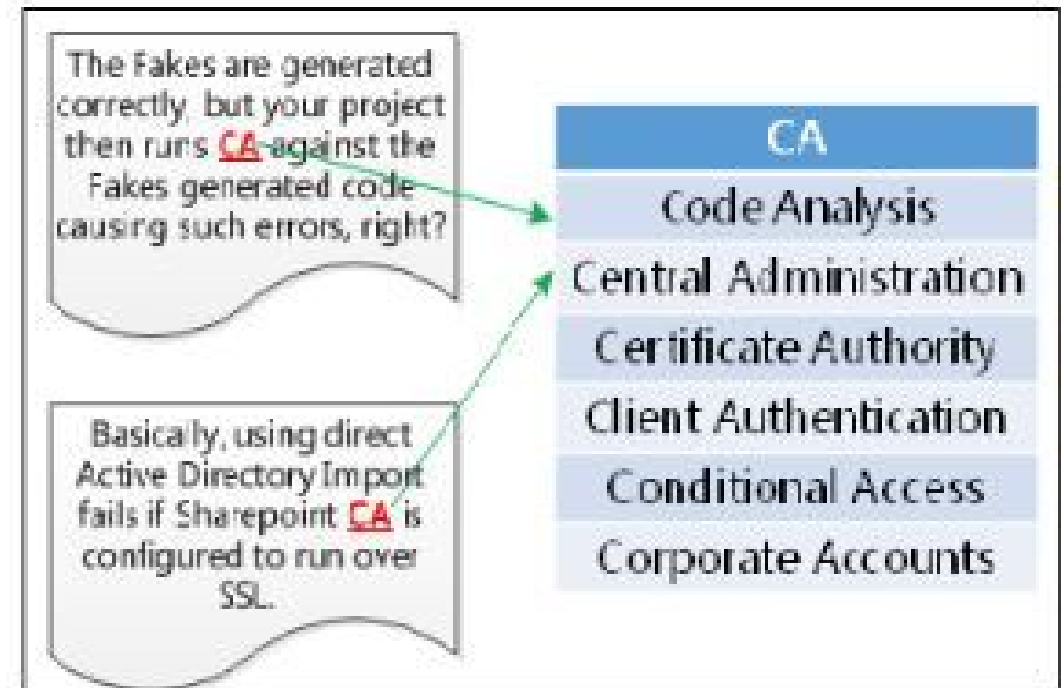
- Many of the relations are vague (e.g., the importance of a skill for a profession).
- As such, their interpretation is **subjective, context-dependent**, and usually **a matter of degree**.
- For that, in our graph, such relations have the following three properties:
  - **Strength**: A number (typically from 0 to 1) indicating the strength/confidence of the relation.
  - **Applicability Context**: The contexts (location, language, industry etc) in which the relation has been discovered and considered to be true.
  - **Provenance**: Information about how the relation has been added to the graph (source, method, process).

# How we use our Knowledge Graph



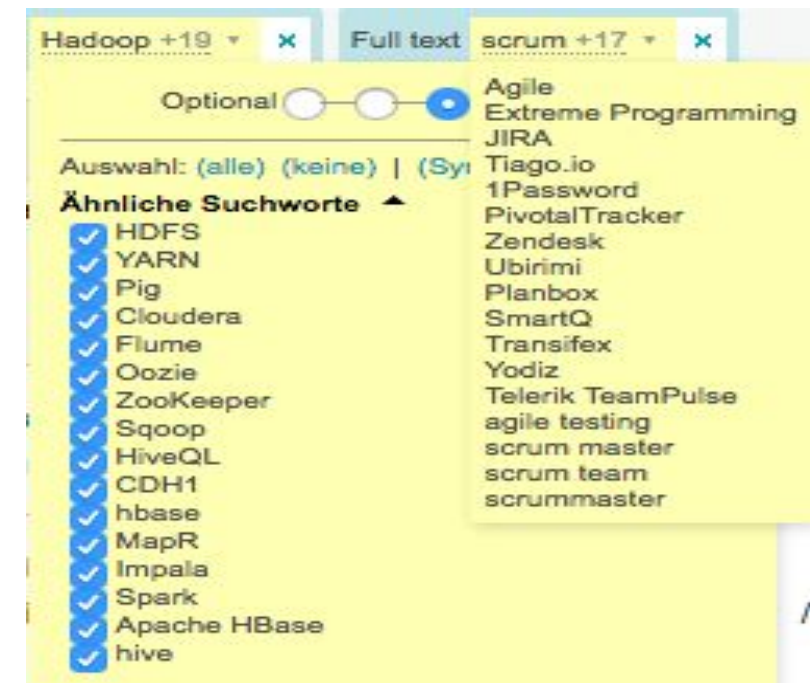
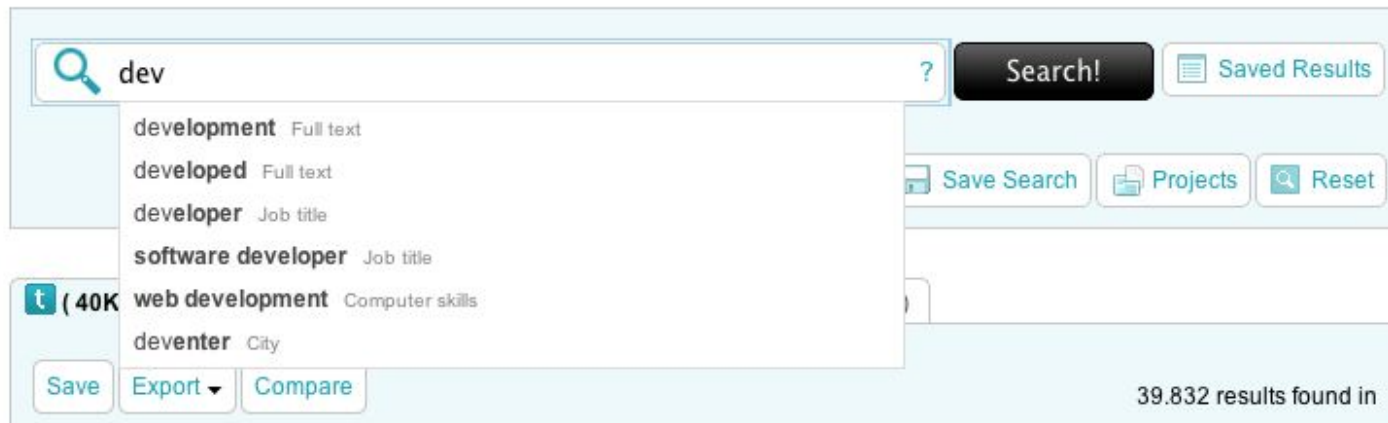
# Extract! CV & Vacancy Parsing

- As Gazeteer for Entity Detection (Skills, Professions, etc.)
- As Contextual Evidence for Entity Disambiguation





- For auto-suggestion
- For expanding queries
- For calculating semantic similarity





# Labour Market Analytics

- Supply-Demand Analysis
- Top Skills per Job
- Career Paths



# How we model Concept Drift

# General principles

- **Concept drift** is typically modeled by means of a concept's:
  - **Labels**, i.e., the words used to express the concept
  - **Intension**, i.e., the concept characteristics as expressed via its properties and relations
  - **Extension**, i.e., the set concept's of the concept's instances
- **In our model:**
  - We do not consider extension
  - We do not consider all properties and relations, nor to the same extent

# Drift in labels and broader/narrower relations

- Changes in labels matter only when they are not merely additions or removals of spelling and/or morphosyntactic variations of existing labels.
- Changes in preferred labels are slightly more important than alternative labels.
- Changes in a concept's broader and narrower relations are important, with broader changes suggesting a more fundamental drift.



# Professions Drift

- Profession meaning is primarily defined by the skills and activities they involve.
- Essential skills for a profession are more important than optional skills.
- Profession meaning also changes, though to a lesser extent, when the industries it is found in change (e.g., journalists start working in the tech sector).
- A profession concept does not drift when the locations or companies it is most popular in, change.

# Skills & Qualifications Drift

- **Skills:**
  - Meaning is primarily defined by their similar skills and activities, as these describe for what tasks and in what contexts a skill is used.
  - It also changes, though to a lesser extent, when it starts being applied in different professions and industries.
- **Qualifications:**
  - Meaning is primarily defined by the skills they develop and/or verify.
  - Secondarily, by the professions they regulate and/or are useful for.

# How we measure Concept Drift

# General approach

- Concept drift is typically detected and quantified by measuring the change in labeling, extension and intension over time.
- In our model:
  - For labeling we use set similarity instead of string one.
  - For vague relations we use metrics that can take in consideration their strength
  - We use parameters to define the particular characteristics of the drift we want to measure (e.g, target concept types, time scope, relation context and provenance.)

# Measuring vague relations drift

- Given two versions of the same concept and a vague relation, we derive the top-N related concepts for each version (based on the strength score)
- Then we calculate their similarity using the generalized Kendall's tau that can measure distance between rankings.
- In that way, for example, if the "Data Scientist" profession continues having the same top 10 related skills but differently ranked, a drift will be detected.

# Measuring drift for different parameters

- **Different parameter values** can yield **different drift**, not only in terms of **intensity** but also in terms of **interpretation**. For example:
  - Using CVs as a relation provenance, the drift reflects the change in the way the workforce side of the labour market interprets and uses the concept.
  - Using only Vacancies, we shall get an idea of how the same concept changes from the industry's perspective.
  - Using news articles, we will measure the change in the general perception of the concept.
  - Using more encyclopedic and definitional data sources (e.g. Wikipedia or specialized dictionaries) may indicate changes in more core aspects of the concept's meaning.

# How we exploit Concept Drift

# Engineering Dimension

- Measuring and monitoring drift helps us quantify and understand better the dynamics of our domain and our graph's content.
- This, in turn, enables us to plan and prioritize the maintenance and evolution of the knowledge graph much more effectively
- For example, we are able to identify highly volatile graph aspects that need more frequent updates, and allocating more resources for that.



# Business Dimension

- Drift in our knowledge graph indicates to a large extent the changes that take in place in the labour market, especially the one that we derive from CVs and Vacancies.
- These changes we can then communicate to job seekers, candidate seekers, education and training providers, policy makers etc.

# Wrapping Up

# Main Conclusions

- The definition and modeling of **semantic drift** for a given knowledge graph **should take into account the graph's content, domain and application context**, and adapted accordingly.
- In order to be able to understand and interpret concept drift better, we need a **versatile measurement framework** that enables the **dynamic and highly configurable measurement and presentation of drift**.

Thank you!



***Dr. Panos Alexopoulos***  
*Head of Ontology*

**E-mail:** [alexopoulos@textkernel.nl](mailto:alexopoulos@textkernel.nl)

**Web:** <http://www.panosalexopoulos.com>

**LinkedIn:** [www.linkedin.com/in/panosalexopoulos](http://www.linkedin.com/in/panosalexopoulos)

**Twitter:** @PAlexop