Applying machine learning tools on web vacancies for labour market and skill analysis

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New tools for analyzing the labour market of the future

- Technology and globalization are radically changing labor markets throughout the world
- Some jobs are disappearing, new jobs are emerging, existing ones are changing.
- In particular jobs' skill requirements is changing considerably.
- Which occupations will grow in the future and where?
- What skills will be needed in the future?
- These are challenging questions that need new tools and new data

Why web vacancies can help

- We need tools able to address the complexity of labor market developments
- We need to focus on skills which are susceptible to change
- We need a data driven approach
- Web vacancies: bottom up approach, real time data, entirely data driven, cheap, very rich
- Surveys (e.g. skill survey): top down approach, pre-defined, expensive, low frequency data

Web vacancies challenges

- Totally unstructured data
- Need classification
- Lots of data, duplication issues
- Representativeness

The Wollybi project

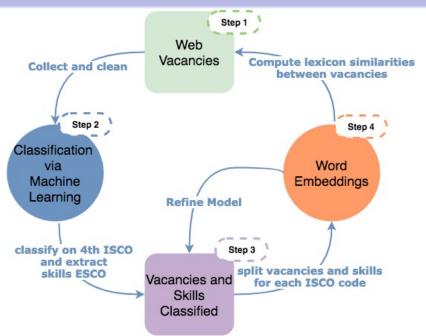
- Since 2013 collects and analyzes web vacancies Italy
- 2.8 millions unique obs analyzed
- Now in charge of a European project funded by Cedefop to implement a European system of LMI.
- By 2018 the project will analyse data from Italy, Germany, France, Spain, UK, Ireland, Czech Rep. (2/3 of EU pop.)
- By 2020 the whole EU will be analysed
- Lots of challenges in a multi language setting!

Wollybi data

- Vacancies
- Job title (ESCO/ISCO)
- Skills (ESCO)
- Additional skills (job requirements)
- Georeferencing (Nuts 4, town)
- Industry
- Education (work experience)

Methods and tools

- Big data tools, (source selection, de-duplication, data cleaning) textual analysis
- Machine learning tools for the classification process
- Skills extraction, n-grams.
- How skill requirement evolve over time? Word embedding (word2vec, doc2vec) to compute index of similarities between skills and vacancies.
- How detect new emerging occupations? LDA



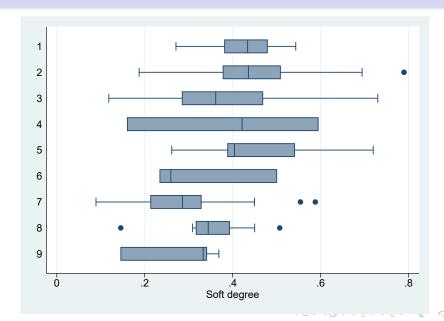
Hard and soft skills

- Hard skills: typically job-specific skills and competences that are needed to perform a specific job or task (e.g. knowledge of specific software or instruments, specific manual abilities etc.)
 - Digital skills are a sub-class of hard skills
- **Soft skills**: transversal competences which refer to the capacity of individuals to interact with others and the environment (e.g. communication skills, problem solving etc.).

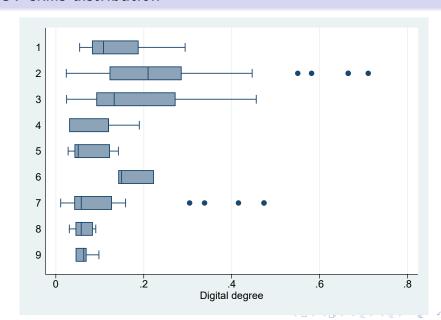
Digital skills

- Information Brokerage skills. Ability to use ICT tools and platforms for data exchange and communication (e.g. social media);
- Basic ICT skills. Ability to use some ICT specific applications for supporting standard individual professional activities (e.g. Office suite);
- Applied/Management ICT skills. Tools and software used within the organisation for supporting management, operational and decision making processes (e.g. administrative software);
- ICT Technical skills. Solutions, platforms and programming languages that are ICT-specific (e.g. programming languages, advanced ICT software).

Soft skills distribution



ICT skills distribution



Explaining the probability of automation

	OLS	W.OLS	OLS	W.OLS
Soft skills	-0.727***	-0.645***		
	(0.122)	(0.001)		
Hard skills			0.842***	0.714***
			(0.118)	(0.001)
Digital skills			-0.719***	-0.683***
			(0.110)	(0.001)
Const.	0.817***	0.759***	0.169**	0.224***
	(0.045)	(0.000)	(0.079)	(0.001)
R2	0.065	0.058	0.137	0.148
N.	512	512	512	512

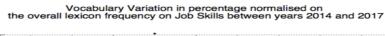
Explaining the probability of automation

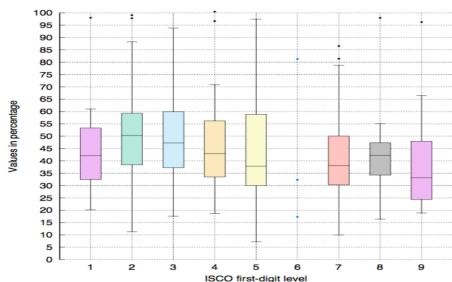
	Q12 Prob	Q34 Prob	Q12 Prob	Q34 Prob
Hard s.	0.589***	-0.008	0.573***	0.016
	(0.106)	(0.048)	(0.105)	(0.049)
Digital s.	-0.493***	0.101**	, ,	,
-	(0.099)	(0.044)		
Inf. Brok.	, ,	, ,	-0.048	0.015
			(0.381)	(0.148)
ICT Technical			-0.694***	-0.190*
			(0.179)	(0.106)
Basic ICT			-1.264***	0.383***
			(0.349)	(0.139)
App. Man. ICT			-0.249	0.052
			(0.183)	(0.093)
Const.	-0.004	0.868***	0.025	0.853***
	(0.064)	(0.034)	(0.067)	(0.036)
R2	0.143	0.021	0.182	0.068
N.	256	256	251	249

How does the skill content of occupation change?

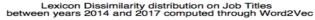
- We have measured the change in description and wording within occupations (4 digit ISCO) between 2014 and 2017
- We have measured the change in vocabulary used for titles and skills
- We have measured the change in *lexicon* used for titles and skills applying the Doc2Vec technique

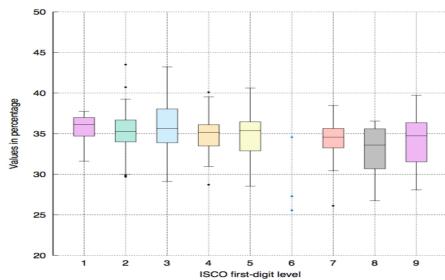
The change in vacancy content: skill vocabulary



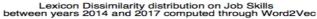


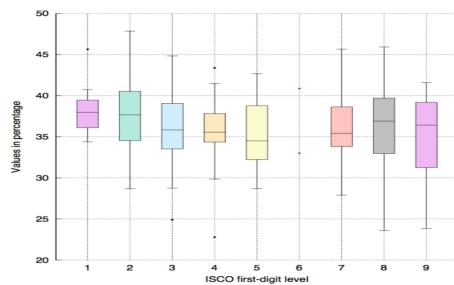
The change in vacancy content: title lexicon





The change in vacancy content: skill lexicon





How to detect new emerging occupations?

- We take vacancy titles by ISCO 4D. We apply LDA (Latent Dirichlet Allocation) which returns returns a list of topics.
- The topics are basically different clustering of words used in vacancy titles with a word probabilistic model.
- Topics are validated by experts which identify new occupations
- The skill set is applied to new occupations

New emerging occupations

New Occ.	Hard Skill	Hard Skill	Hard Skill
	ICT (50.32%)	Maths&Stats (29.60%)	Bus.&Admin. (19.33%
DI Amaluet	SQL & Oracle	Data Analysis	Public Relations
BI Analyst	SharePoint		Management
	Data Integ*		Manage Quality?
	Maths&Stats (48.15%)	ICT (29.01%)	Bus.&Admin.(22.84%
Data Scientist	Data Analysis	SQL & Java	P.R.
Data Scientist	SAS	Business Intell.	Management
!	SAP & SPSS*	Data Integration*	Customer Rel. Manag
	Bus&Admin.(48.07%)	ICT (19.89%)	Law (16.02%)
Caellini, Man	Management	MS Office	Security Law
Facility Man.	Public Relations	AutoCAD	Legal Studies
	Negotiation exp	Basics ICT	
	Law (41.51%)	ICT (28.30%)	Bus.&Admin. (16.989
LICE Case	Security Law	Basic ICT	Manage Quality
HSE Spec.	Legal Studies	SAP CRM	Industry Systems

New emerging occupations

New Occupation	Soft Skill	Soft Skill	Soft Skill	Soft Skill
BI Analyst	Foreign languages (39.23%)	Positive attitude (31.51%)	Problem solving (15.35%)	Cooperation with others (6.27%)
Data Scientist	Positive attitude (38.58%)	Foreign languages (29.63%)	Problem solving (13.58%)	Cooperation with others (6.79%)
Facility Manager	Foreign languages (39.68%)	Positive attitude (28.95%)	Leadership ability (16.09%)	Problem solving (11.53%)
HSE Specialist	Foreign languages (14.55%)	Problem solving (56.36%)	Positive attitude (20.00%)	Cooperation with others (3.64%)