KID SUMMER SCHOOL
Knowledge Dynamics, Industry Evolution, Economic Development

Teamwork dynamics in scientific knowledge production

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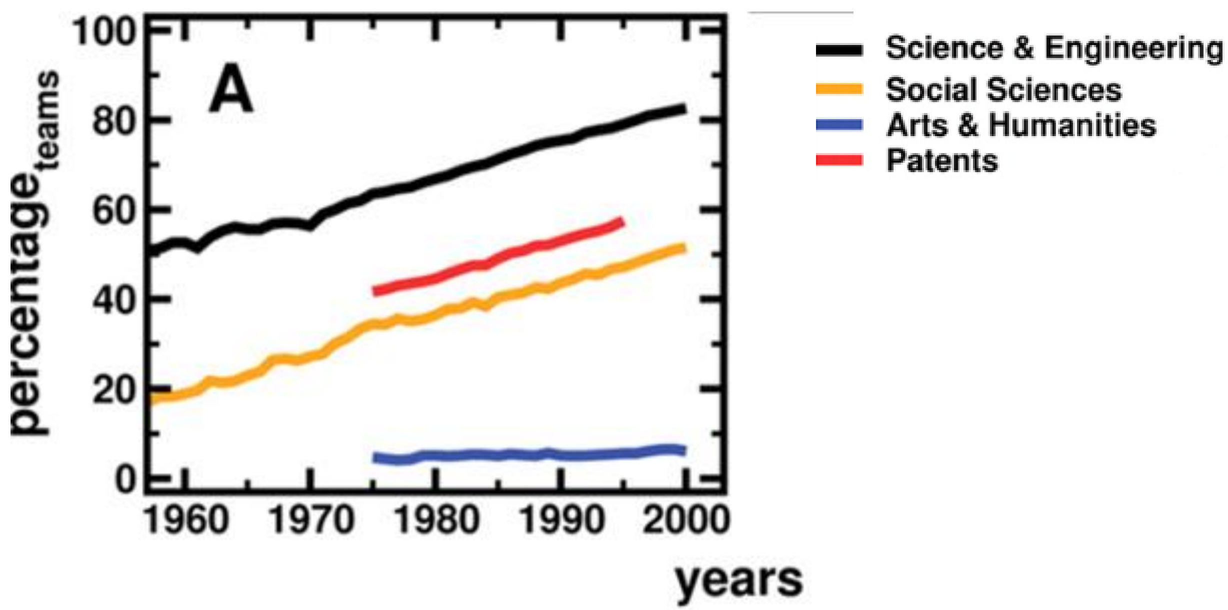
7th July 2017, Nice, France

Scientists are increasing working in teams: A trend in scientific knowledge production



The Growth of Teams

Source: Wuchty S., B.F. Jones, and B. Uzzi, 2007

Scientists are increasing working in teams: Reasons behind the trend

- High cost of scientific instrumentation leads scientists to organize in teams to share resources and avoid cost duplications;
- Low travel and communication costs increase scientists' mobility and favor the creation of multi-institution teams;
- High level of complexity in science leads scientists to organize in teams to solve problems joining specialized competences

Scientists are increasing working in teams: Unexplored aspects

- Individual gains of teamwork:

  - *What is the optimal team composition that favor individual learning from other team members?*

- Aggregated gains of teamwork:

  - *What is the optimal team composition that favor aggregated team productivity?*

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At the origins of learning: Absorbing knowledge flows from within the team

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Journal of Economic Behavior & Organization

(with Charles Ayoubi and Michele Pezzoni)

At the origins of learning: Absorbing knowledge flows from within the team

Motivation

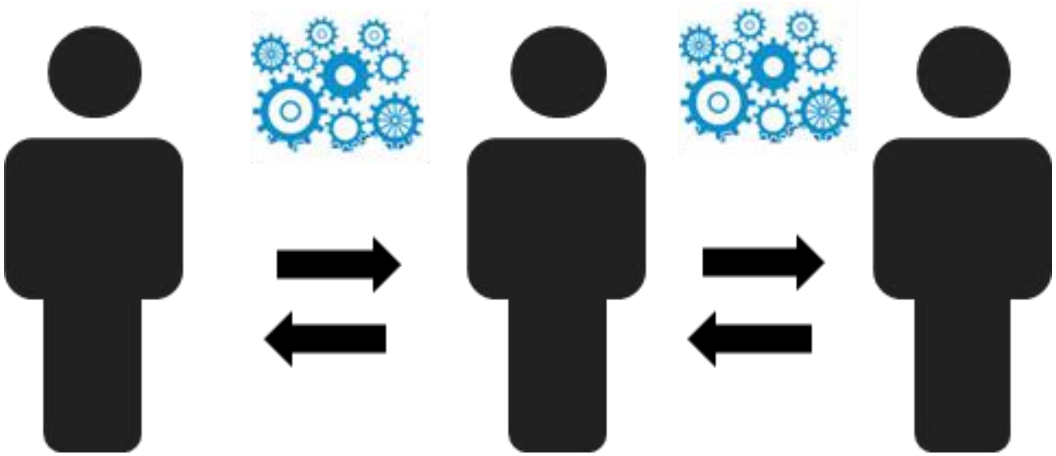
- Teamwork is positively valued for the production of knowledge: each member brings her knowledge and skills in order to solve complex problems (Wutchty et al., 2007)

  - Working in team: individuals have the occasion to learn one from each other (Katz and Martin, 1997)

  - So far there are no studies that identify knowledge flows within a team

Our research question

What are the determinants that allow an individual to learn from other team members?



Our contribution

We look at individual learning (knowledge acquisition) when scientists are working in a team

- We add to Science of Team Science literature, an emerging area of research centered on examination of the processes by which scientific teams organize, communicate and conduct their research (Börner et al., 2010; Stokols et al., 2008; Whitfield, 2008)

In a nutshell

1. We identify teams

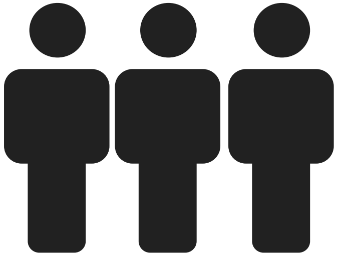
2. We provide a novel measure of learning

3. We isolate the portion of learning originating from within the team

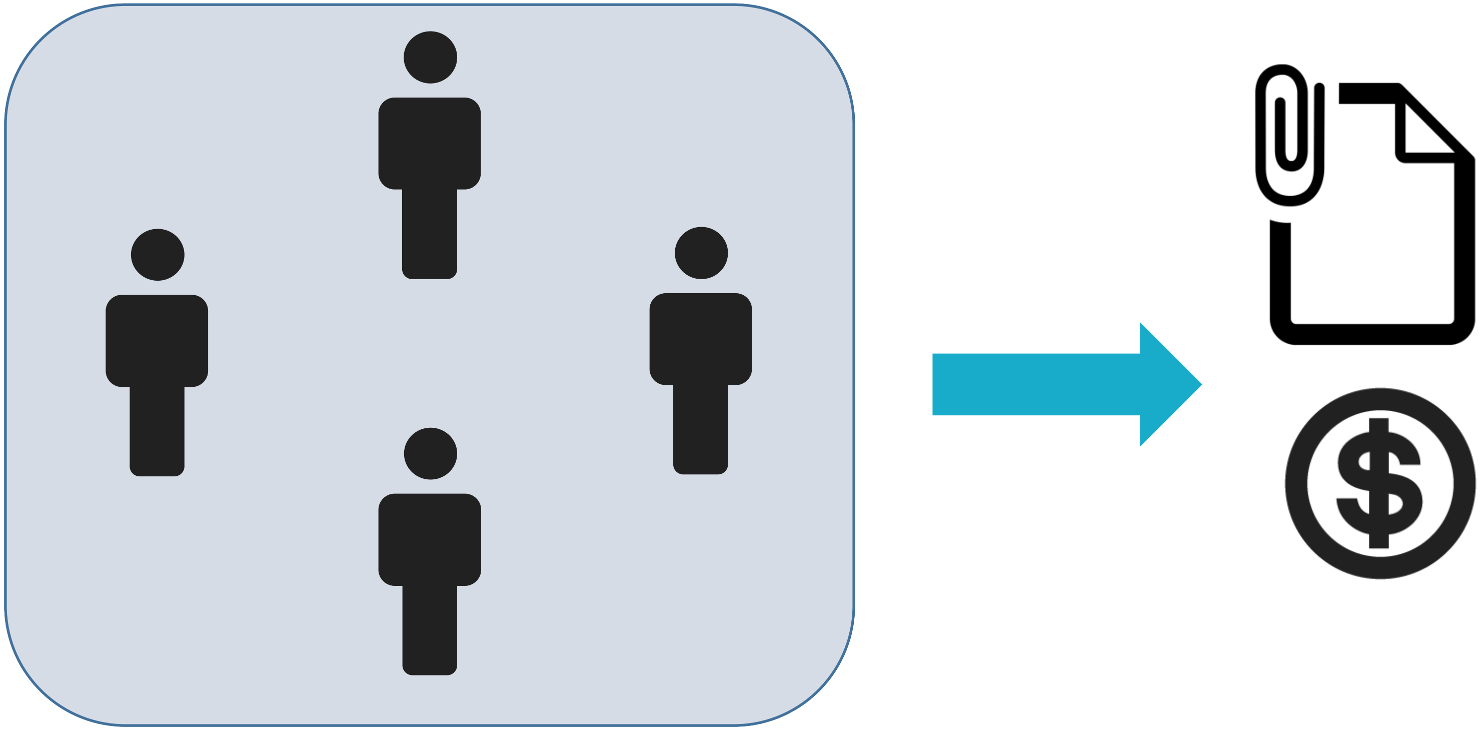
4. We identify the determinants of the individual learning

1. Identifying a team

- A team is defined as a group of individuals working together to achieve a common goal (Katz and Martin, 1997)

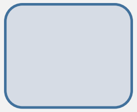


TEAM=All applicants submitting a common grant application



Legend:

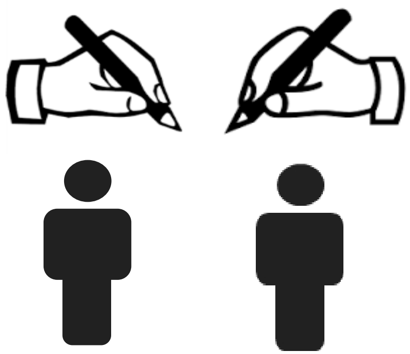
Team member



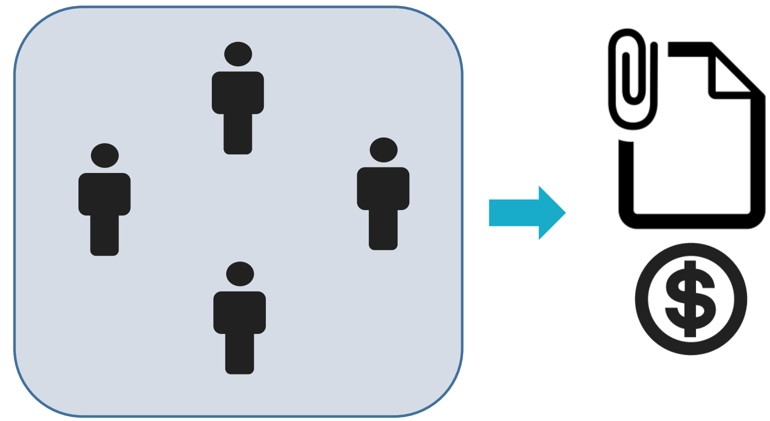
Team boundaries

Grant application

Co-author teams vs. grant application team



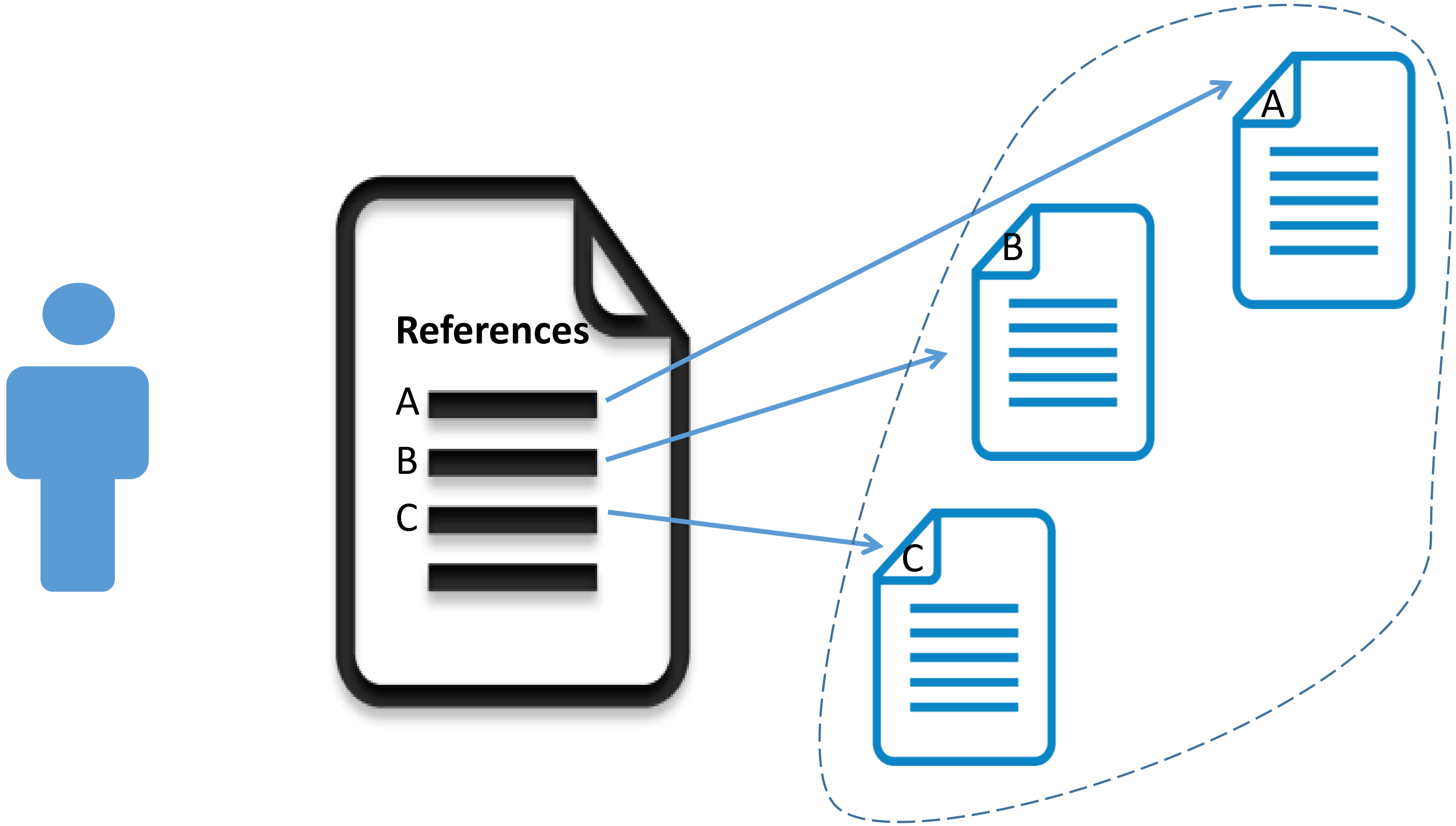
Vs



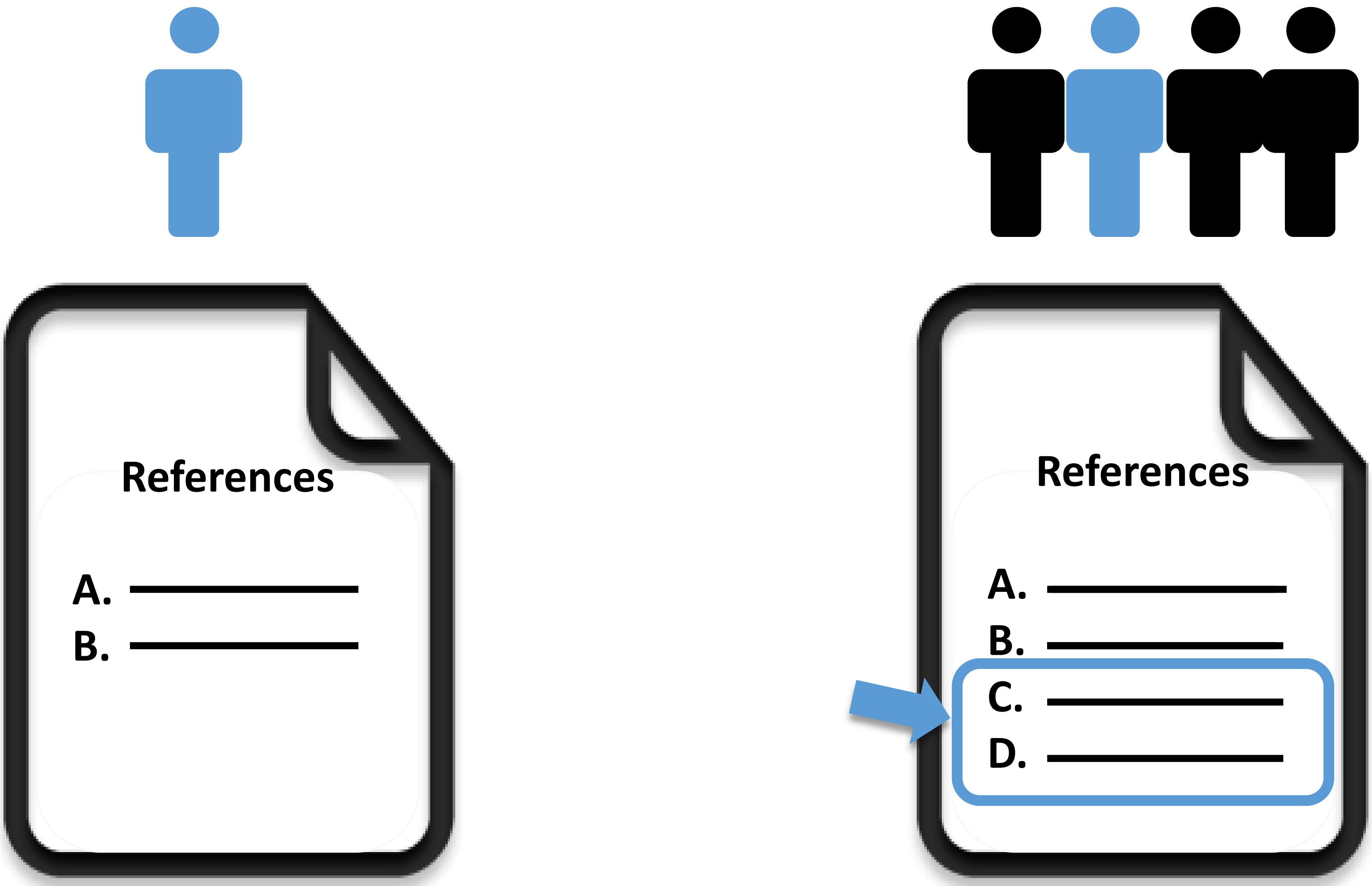
Team definition based on co-authorship	Team definition based on grant application
Only successful collaboration	Successful and unsuccessful collaborations
Collaborations start when the first outcome appears	Collaborations start when the applicants express their willingness to collaborate by submitting the application
Collaboration achievements cannot be identified	Collaboration goals are declared in the application

2. Providing a novel measure of learning

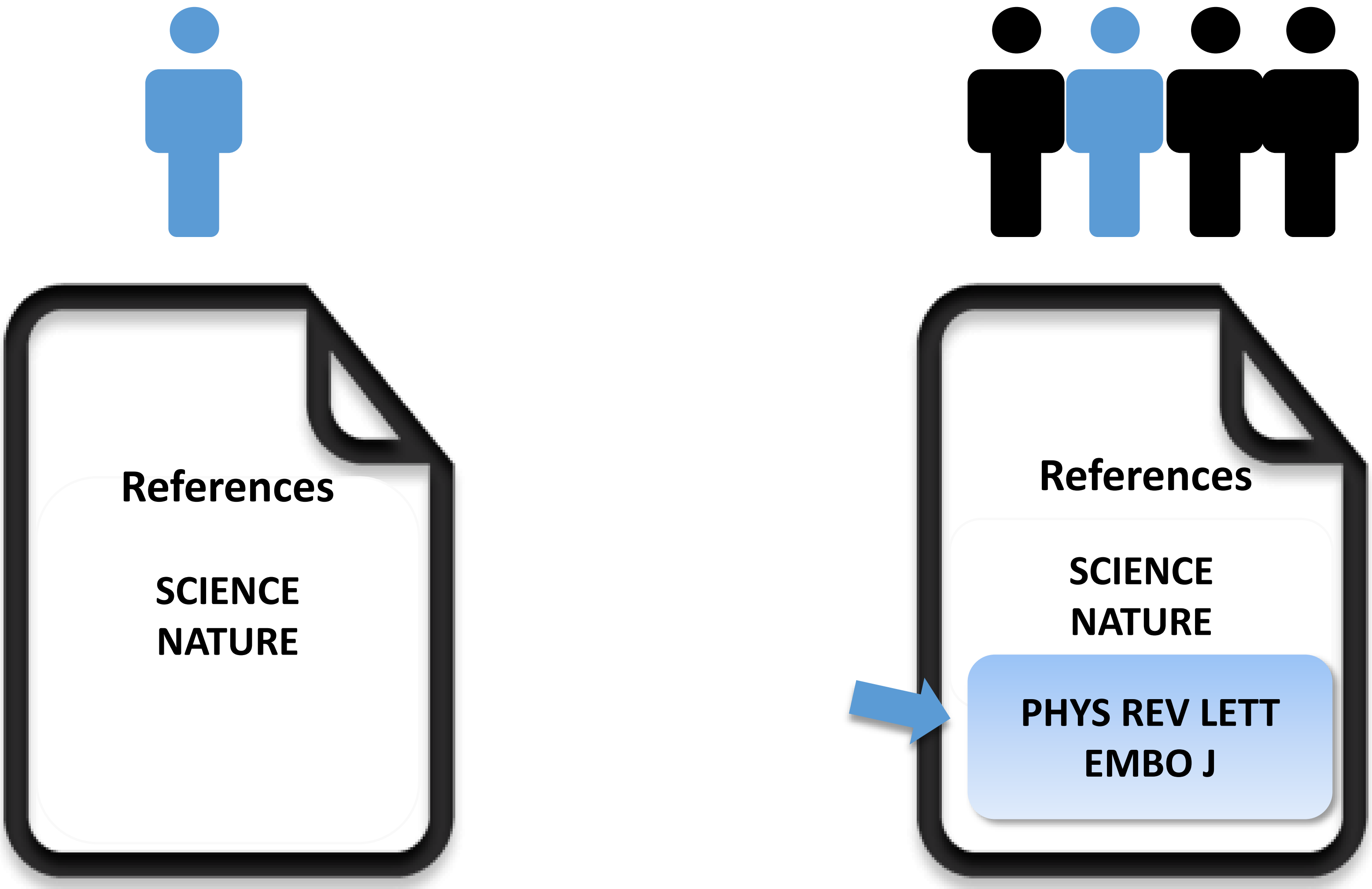
a. What is cited = Knowledge stock of researcher



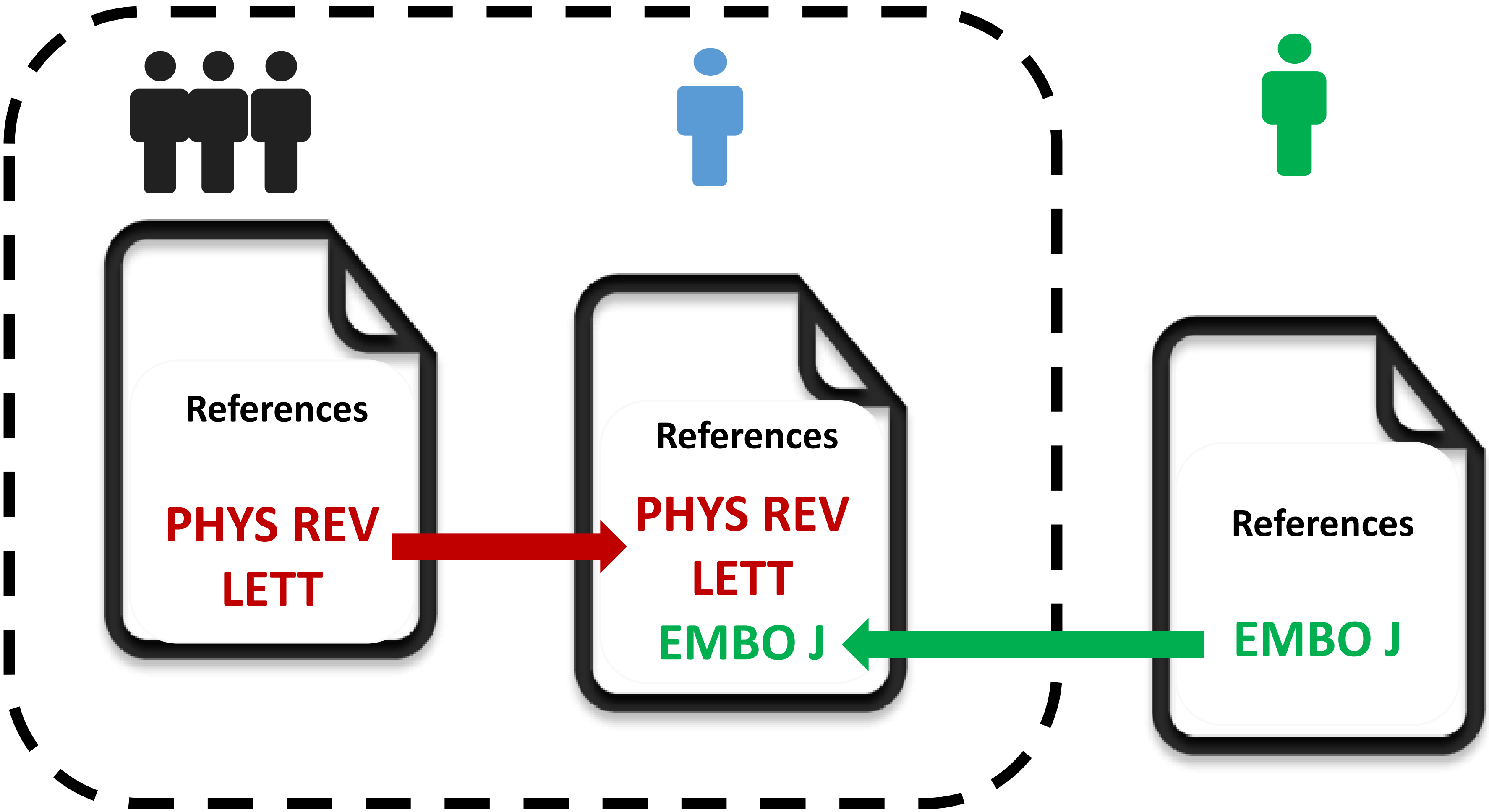
b. New citations = Individual learning



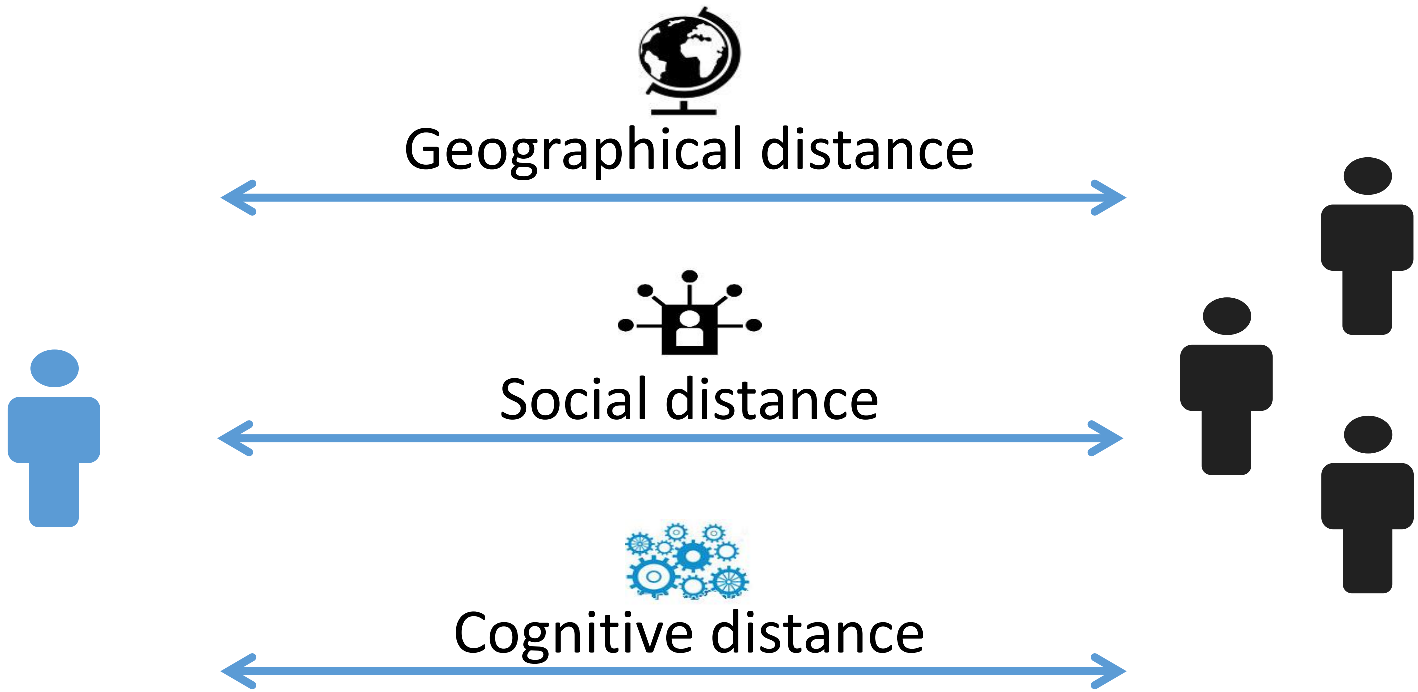
b. New citations = Individual learning



3. Isolating the portion of learning originating from within the team

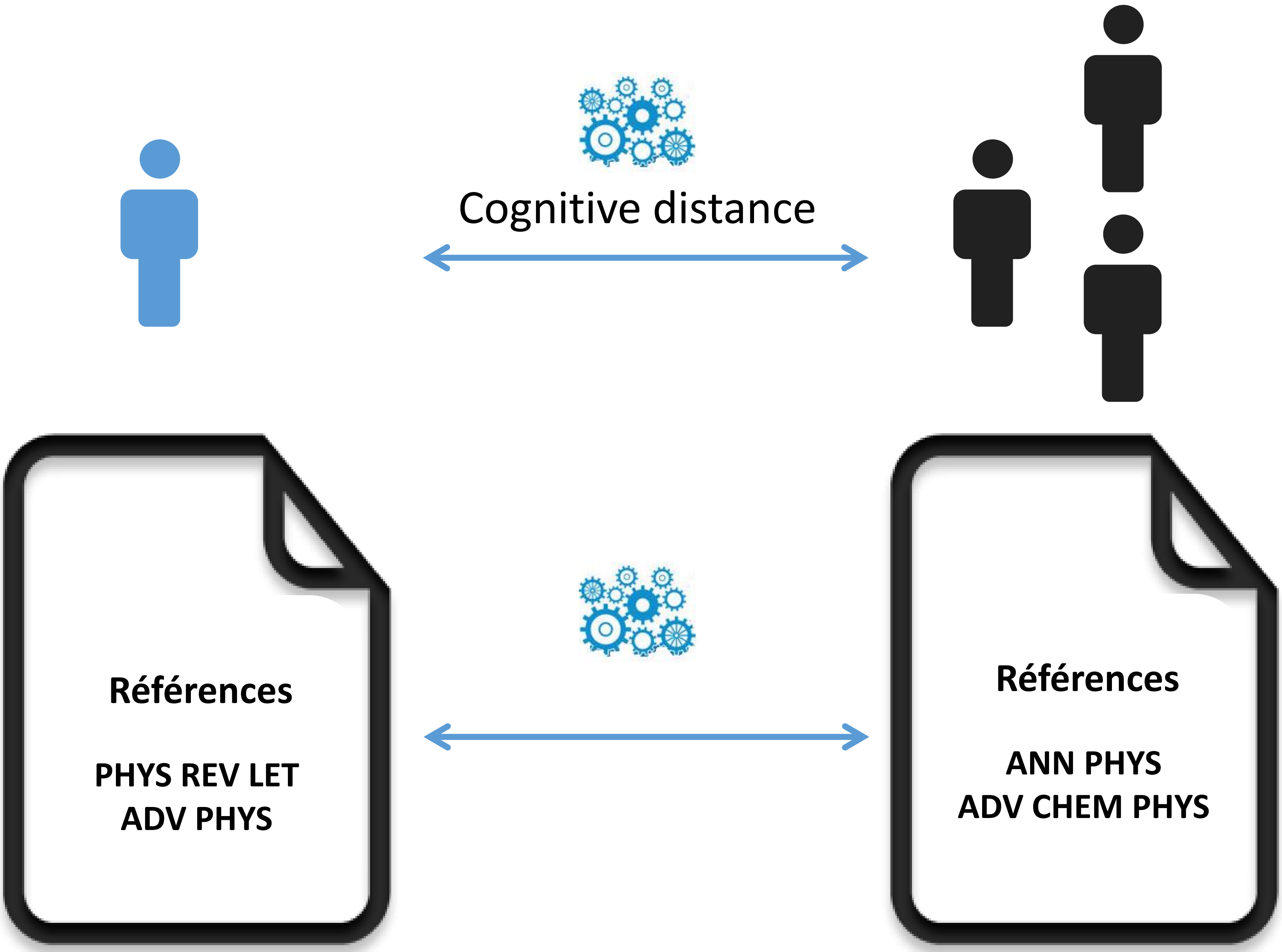


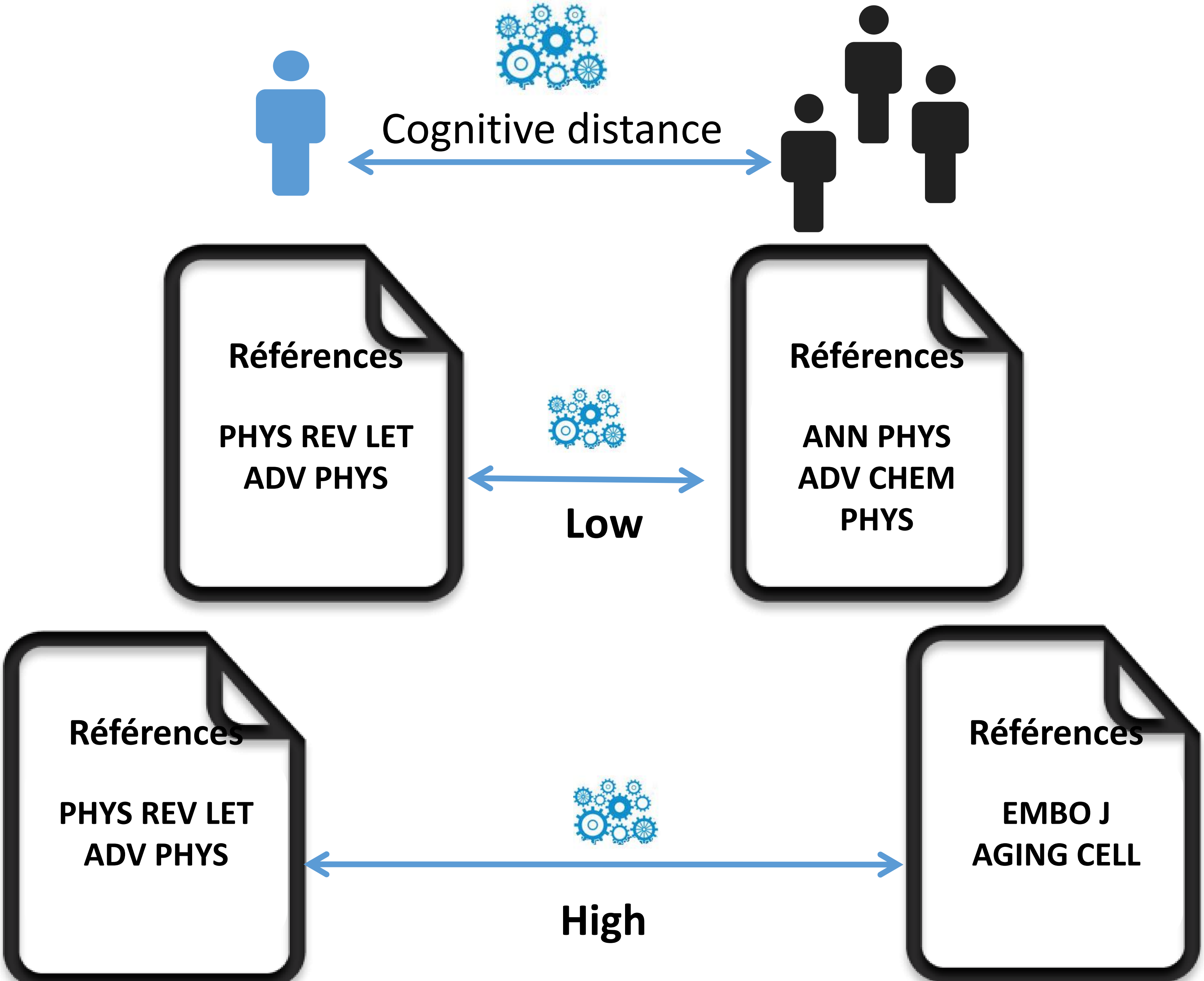
4. Identifying the determinants of the individual learning



***Pr*(Individual learning within team)= *f*(Geographical distance, Social distance, Cognitive distance + Controls)**

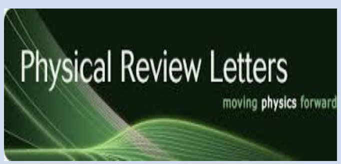
Where controls are individual, team and journal characteristics


Cognitive distance
Références
PHYS REV LET
ADV PHYS
Références
ANN PHYS
ADV CHEM PHYS


Cognitive distance
Références
PHYS REV LET
ADV PHYS
Références
ANN PHYS
ADV CHEM
PHYS
Low
Références
PHYS REV LET
ADV PHYS
Références
EMBO J
AGING CELL
High

Cognitive distance: First step

If two journals are frequently co-cited within the article reference lists, the two journals are close

Journal distance matrix			
	0	3.88	163.39
	3.88	0	1.31
	163.39	1.31	0

Cognitive distance: Second step

We use the Journal Distance Matrix to calculate the average distance between the journals cited by the focal individual (A) and the journals cited by the rest of her team (T)

$$D_{A,T} = \sum_{i=1}^{\#A} \sum_{j=1}^{\#T} D(i,j)/(\#A * \#T)$$

Where:

i = Journal cited by the focal individual (A)

j = Journal cited by her team (T)

#A = Count of journals cited by A (before the application)

#T = Count of journals cited by the other team members (before the application)

The SINERGIA Program: A novel empirical setting

- Aim:
  - Promote collaboration
    - Inter-disciplinary teams
    - Same-discipline teams
- One of the funding schemes of the Swiss National Science Foundation (SNSF)
- Introduced in October 2008 (our sample 2008-2012)

Our sample: scientist’s profile

- Number of scientists: 780

	Mean	**Std. Dev.**	**Min**	**Max**
Age	47.44	8.07	30	69
Gender (=1 for female, 0 otherwise)	0.16	0.36	0	1
Stock of publications pre-team entry	37.58	34.29	1	318
Stock of journals cited pre-team entry	135.62	102.24	1	644

Our sample: Team profile

- Number of Teams: 255

	Mean	Std. Dev	Min	Max
Number of team members	4.19	1.59	2	11
Number of nationalities represented	2.64	1.08	1	7
Engineering	0.36	0.48	0	1
Science & Medicine	0.64	0.48	0	1
Number of disciplines	3.30	2.16	1	11
Average team members' age	47.74	4.93	35.09	59.97
Share of women	0.15	0.21	0	1
Average team members' stock of pubs	43.18	24.75	2.84	153.65
Awarded	0.45	0.5	0	1
High quality application (grade A)	0.09	0.28	0	1
Low quality application (grade D)	0.15	0.36	0	1
Amount requested	1,674,320	764,260	349,901	6,854,573

Results probit estimation: Marginal effects

Dependent Variable: **Pr(Individual Learning within Team)**	Papers co-authored are included	Papers co-authored are excluded
A. Team Characteristics		
Co-ethnic team	0.012	-0.008
At least one female scientist in the team	-0.012	-0.017
Awarded	-0.018	-0.023*
High quality application (grade A)	0.032	0.022
Low quality application (grade D)	-0.032*	-0.026
Log(Amount requested)	0.075***	0.067***
Log(Number of team members)	0.26***	0.26***
Log(Number of sub-disciplines)	0.024***	0.020***
Science & Medicine	0.066***	0.066***

Table to be continued (next slide)

Results probit estimation: Marginal effects

Dependent Variable: **Pr(Individual Learning within Team)**	Papers co-authored are included	Papers co-authored are excluded
B. Team-individual distance		
Social Distance		
Same gender scientist vs. team	0.029	0.031
Standardized stock pub. difference scientist vs. team	-0.100***	-0.100***
Standardized age difference scientist vs. team	-0.013	-0.014
Established collaboration	0.058***	0.046***
Geographical distance		
Log(1+Hr distance)	0.008	0.009
Cognitive distance		
Log(Cognitive distance)	0.55***	0.45**
Log(Cognitive distance)^2	-0.064***	-0.055***
C. Individual characteristics	Yes	Yes
D. Journal characteristics	Yes	Yes
Pseudo R^2	0.12	0.11
Observations (Scientist-Journal cited pairs)	118,602	106,898

Individual and journal characteristics

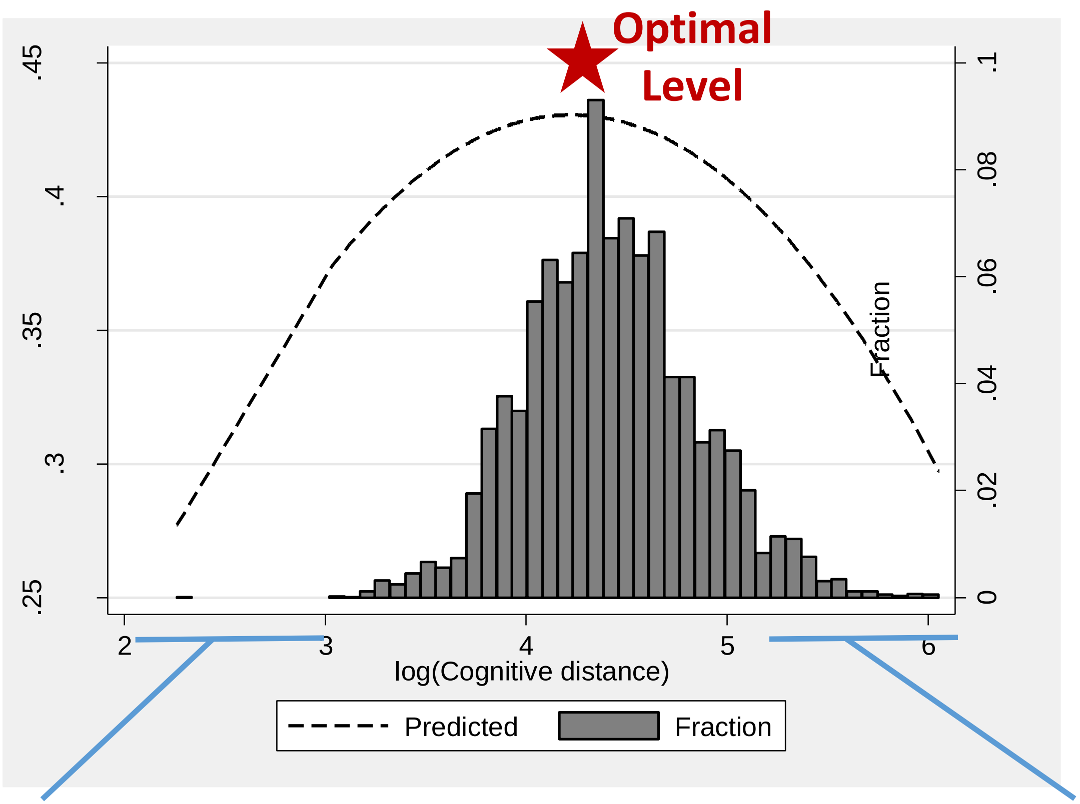
C. Individual Characteristics

- Gender
- Age
- Past productivity

D. Journal Characteristics

- Journal frequency: Count of articles citing the focal journal
- Generalist: Dummy equal to 1 for a generalist journal
- Journal age: Count of years since journal first publication
- Unknown history: Dummy equal to 1 if history of journal is missing

Is there an optimal level of cognitive distance?



Individuals share the same knowledge.

Individuals ‘speak a different language’.

Main contributions

- We identify the building blocks of the knowledge capital stock and we follow knowledge flows from one individual to another one

- We find that scientists' characteristics vs. the rest of the team affect individual learning within the team

Policy implications

- In promoting teamwork particular attention should be devoted to team composition

  - Previous experience of joint research work favors learning ☺
  - The presence of highly productive scientists in the team favors learning for less experienced scientists ☺
  - Having an established collaboration with the other teammates favors learning ☺
  - High levels of discipline diversity could have unintended consequences for learning ⚠

IEEE Transactions on Engineering Management

(with Annamaria Conti and Olgert Denas)

Knowledge Specialization in Ph.D. Student Groups

Research question

- How does task specialization in research-intensive teams affect productivity?
  - Does it pay for teams to be organized like bees in a hive, with each team member performing a specific task?

In a nutshell

1. We identify teams

2. We provide a novel measure of knowledge specialization

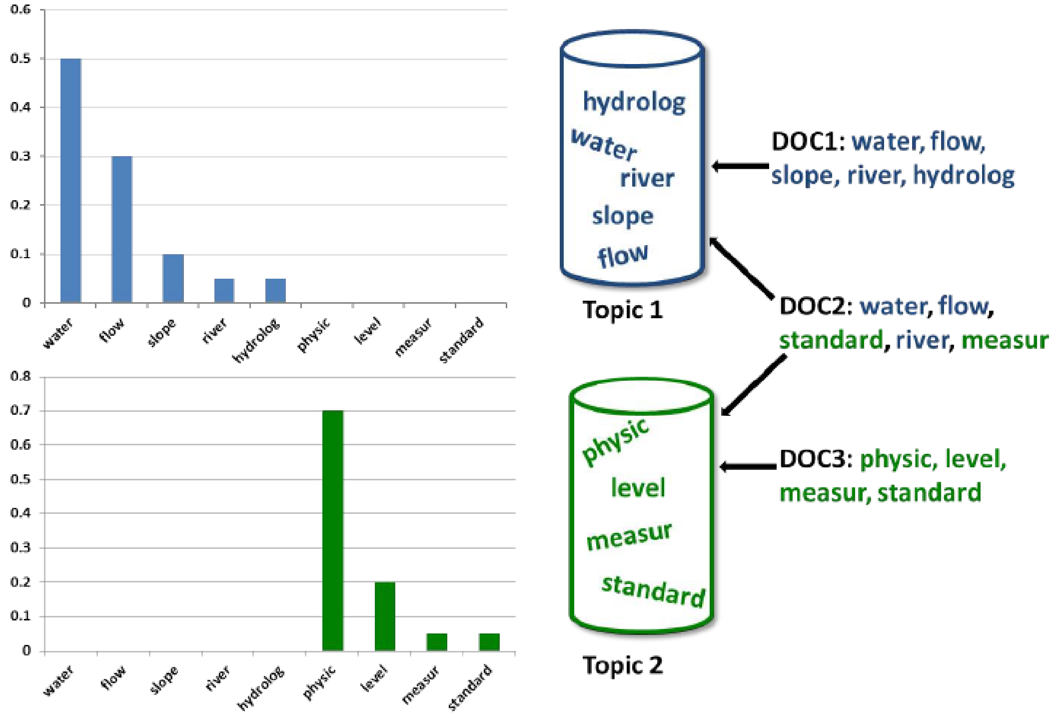
3. We identify the relationship between knowledge specialization and team productivity

1. Identifying a team

- A group of PhD students supervised by the same professor in year *t*, whose research organization is set by their supervisor and whose ultimate goal is to maximize research output

2. Providing a new measure of knowledge specialization: First step

- We extract Ph.D. students' research topics from dissertation abstracts (Latent Dirichlet Allocation method)



2. Providing a new measure of knowledge specialization: First step

Topic16 *terms*	Topic 21 *terms*	Topic 25 *terms*
WATER	PHYSIC	POLYM
FLOW	DECAI	POLYMER
SLOPE	LEVEL	CHAIN
RIVER	MEASUR	STABIL
HYDRAUL	CP	CONCENTR
SEDIMENT	STANDARD	MONOM
FLOOD	EXPERI	VISCOS
HYDROLOG	BS	DISPERS
NATUR	DETECTOR	COPOLYM
CATCHMENT	THEORI	ENCAPSUL

Topic 73 *terms*	Topic 99 *terms*	Topic 111 *terms*
ION	FREQUENC	NUMER
COMPOUND	PERIOD	EQUAT
EXCHANG	RESON	SOLUT
METAL	OSCIL	METHOD
SOLUT	AMPLITUD	FINIT
STABIL	EXPERIMENT	NONLINEAR
PH	MEASUR	SPACE
IONIC	NONLINEAR	ELEMENT
RELAX	HARMON	APPROXIM
PROTON	RING	LOCAL

2. Providing a new measure of knowledge specialization: Second step

- Herfindahl Index applied to topic counts:

$$Team\_Specializ\_Abs = 100 \times [1 - \sum_t \left(\frac{c_t}{T}\right)^2]$$

- where:

c_t= # of documents in which a topic appears

$T = \sum_t c_t$

- Index varies between 1 and 100,

larger value implies ↑ of task specialization

3. Identifying the relationship between knowledge specialization and team productivity

Dependent Variable:	**N. Pubs (t+1)**	**N. Pubs (t+2)**
Within-group specialization (N)	0.030***	0.032***
Within-group specialization (N) ^2	- 0.001**	- 0.001**
Characteristics of the PhD student group	YES	YES
Characteristics of the group's supervisor	YES	YES
Characteristics of the department	YES	YES
Characteristics of EPFL	YES	YES
Observations	1938	1938
Log-likehood	-3638	-3645

Characteristics of the PhD student group

- Group size
- Group research breath
- Mean group tenure
- N students with research award
- Mean group age
- Std dev group age
- Master background diversity
- Thesis is co-supervised
- Professor PhD group publication (t-1)

Characteristics of the group’s supervisor

- Professor age
- Professor nationality
- Professor knowledge capital stock
- Professor publications
- SNSF grants

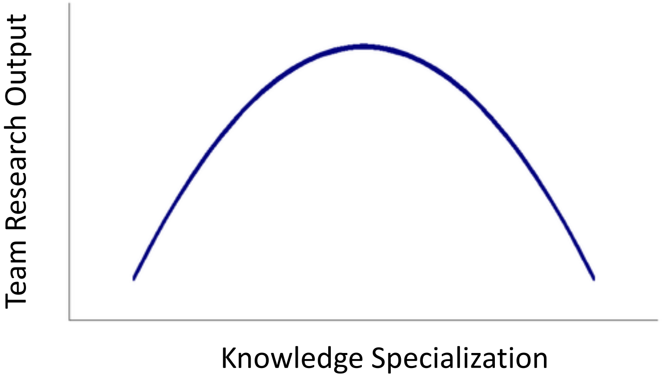
Other controls

- Characteristics of the department
  - Department funds
  - Department fixed effect

- Characteristics of EPFL
  - Time trend

Main finding

- The relationship between knowledge specialization and research output has an inverted U-shaped form, as indicated by the negative and statistically significant coefficient of the squared term of *Within-Group Specialization (N)*



Managerial and policy implications

- From a managerial perspective, our results have implications for the optimal design of firms' research-intensive groups
- From a policy perspective, our results have important implications because they shed light on the functioning of the Ph.D. student groups, whose contributions to a country's innovation capacity have been widely recognized

What’s next? Hints for future research in the area

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Chiara Franzoni, Giuseppe Scellato, Paula Stephan

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http://www.nber.org/workinggroups/ipe/ipe_researchproject.html: Global Science project (scientists across 16 countries in 4 research fields)

Thank you for your attention!

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