



Modeling Task Complexity in Crowdsourcing

Jie Yang, Judith Redi, Gianluca Demartini, Alessandro Bozzon



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Task Properties in Crowdsourcing

- Studying *task properties* is key for addressing core crowdsourcing problems such as *task assignment*, worker retention and reliability (Yang and Bozzon 2016)
- Work exists on properties such as compensation and execution time,
 - which are typically related (piecework?)
- What about complexity?

—— one of the most important task properties



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Depends on



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- Depends on
 - Intrinsic property of a task



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 Perceived task complexity can influence the task selection strategy of workers, as well as the quality of their performance

Research Question

Can we measure (and predict) perceived task complexity based on task design characteristics?

Modeling Task Complexity

Observe subjective perception of task complexity

- Instantiate a bunch of different tasks
- Ask workers to carry them out and evaluate their complexity

Map features into subjective perception

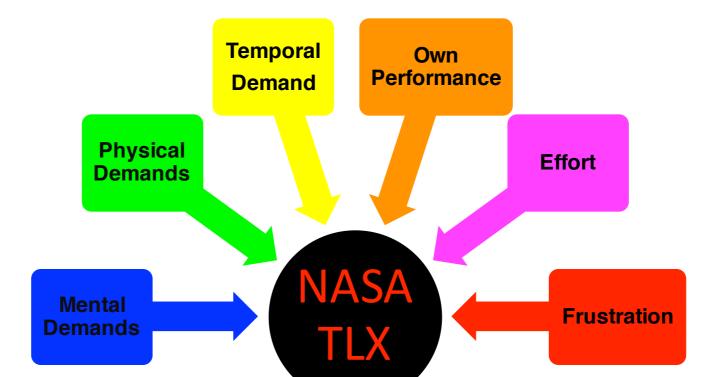
Regression



Metadata Semantics Visual

Subjective Task Complexity Evaluation

- Perception of the level of complexity associated with the action of performing of a task
- Crowdsourcing experiment to measure subjective task complexity
- NASA Task Load Index (TLX): complexity factors and weight
 - Overall complexity = weighted sum of all complexity factors



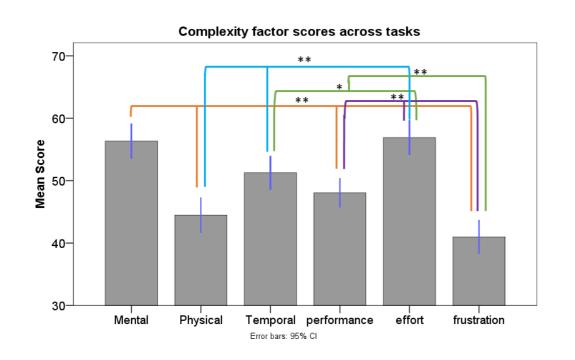
Tasks

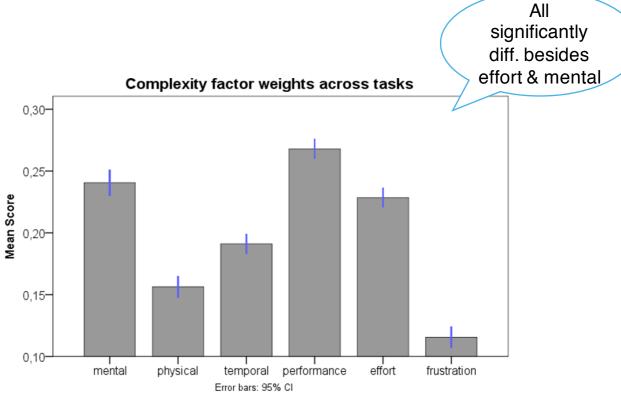
- Dataset of 61 real mTurk Tasks
 - Crawled through extension of the mTurk-tracker to retrieve metadata, formatting (JS, CSS) and MM content if applicable
 - One week observation: from each requester 1 task per type

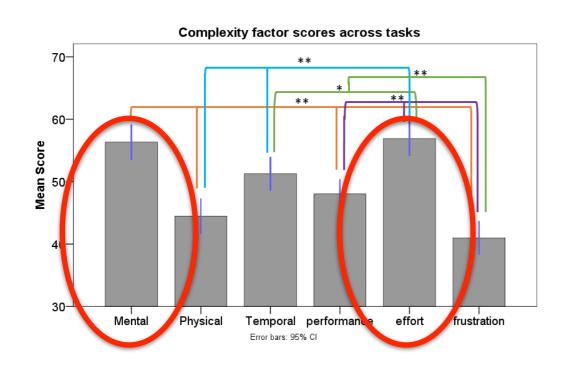
Task Type	Count	Percentage
Survey (SU)	4	7%
Content Creation (CC)	19	31%
Content Access (CA)	4	7%
Interpretation and Analysis (IA)	17	28%
Verification and Validation (VV)	2	3%
Information Finding (IF)	14	23%
Other	1	2%

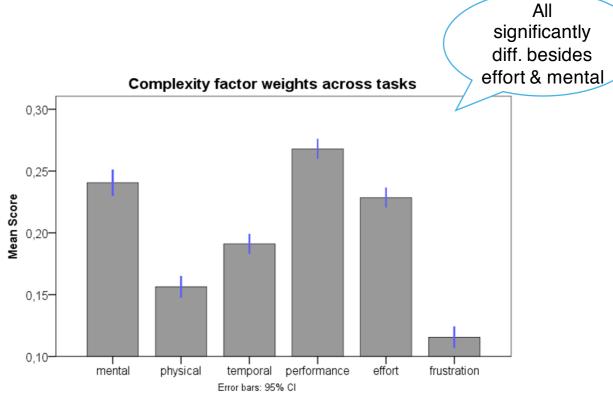
Experimental Setup

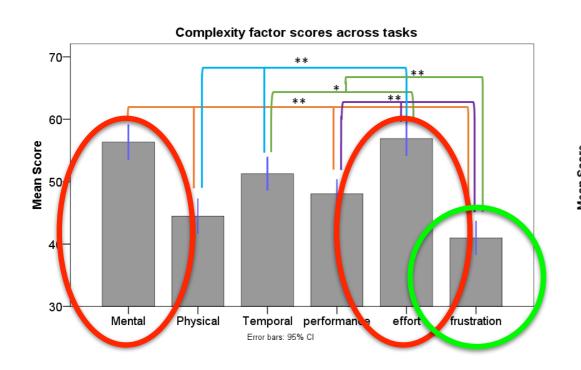
- Protocol: Task execution + TLX (referred to the task just executed)
 - Evaluation Tasks were re-instantiated in CrowdFlower
 - TLX was appended at the end of concluded tasks
- Tasks were executed and evaluated by min 13 and max 16 workers (903 evaluations in total)
- Filtering
 - 3 control questions, 2 mistakes = out (15% of the evaluations discarded)
 - Completion time, too long or too short = out (6% of the evaluations discarded)

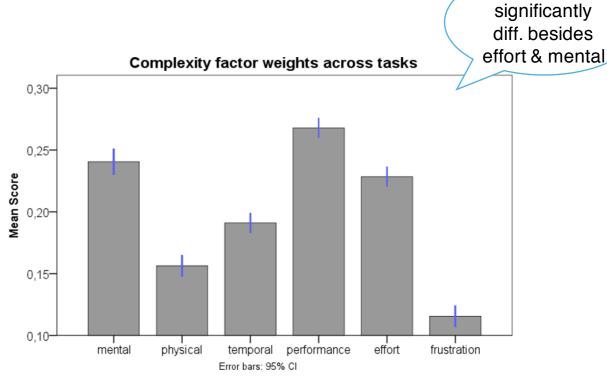




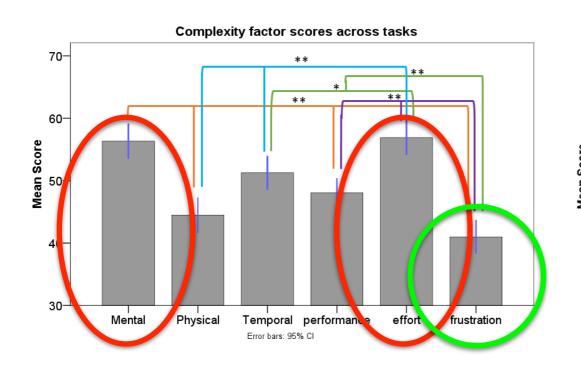


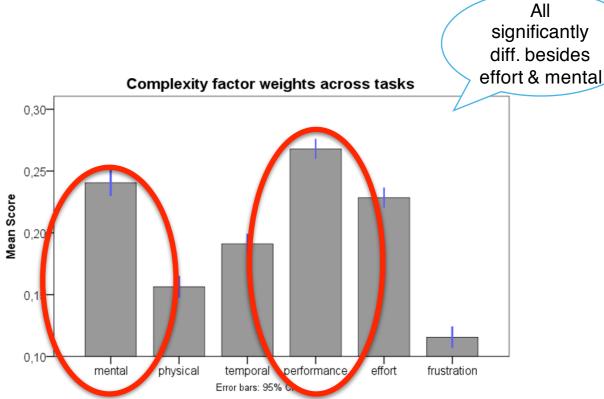


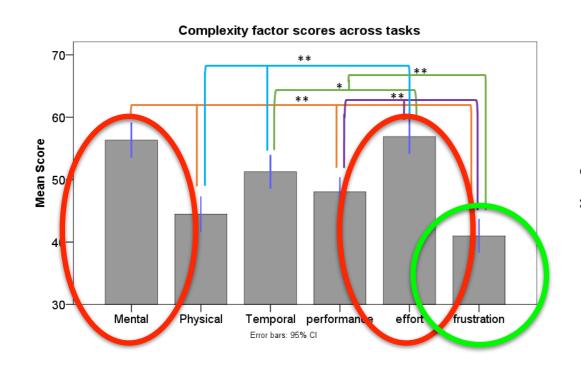




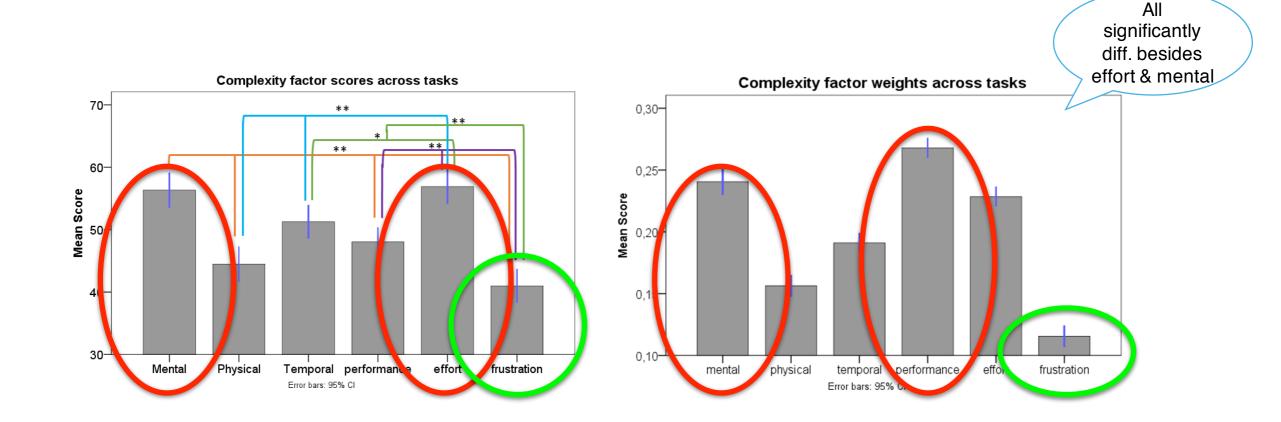
ΑII









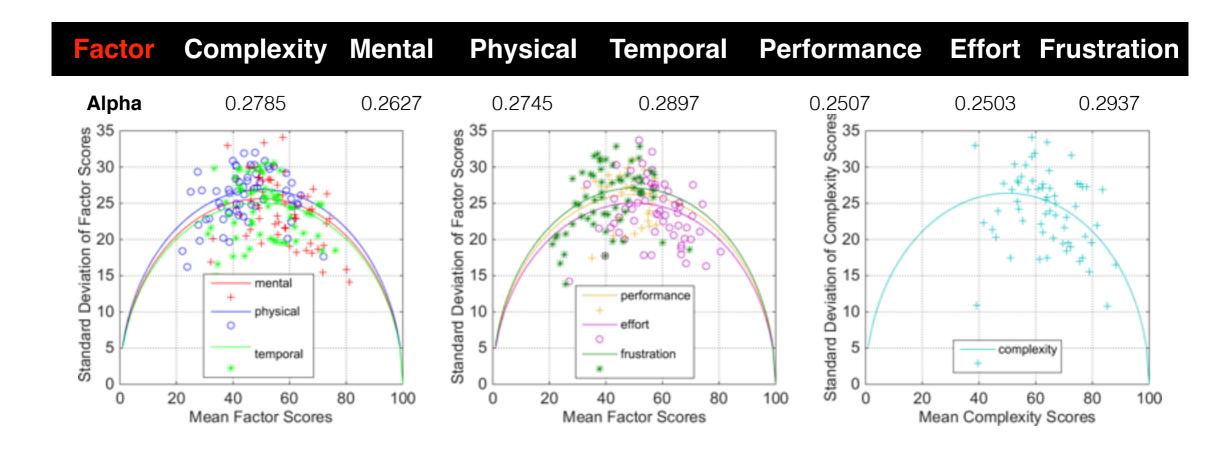


Mental demands and effort are mostly perceived task complexity factors; and workers care about their performance

Reliability of Scores

—— SOS Analysis

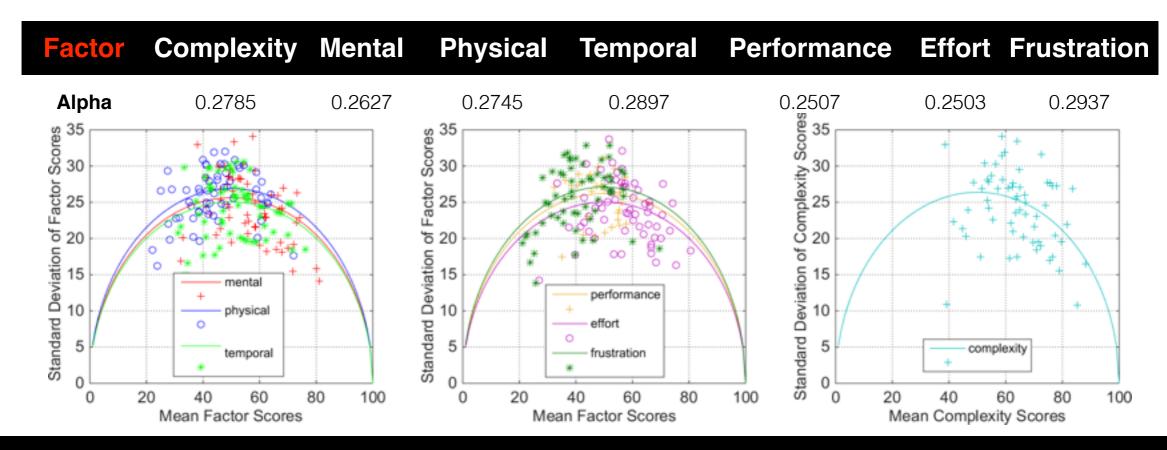
- SOS hypothesis: Mean Opinion Score (MOS, e.g. mean complexity, or complexity factor score) and the spreads of individual scores (SOS) are linked by a squared relationship
 - Useful in subjective assessment involving a pool of participants scoring the same item
 - Alpha: variability in evaluations



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Modeling Complexity: Task Features

Metadata (9)

- Title length
- Description length
- Required worker location
- Required Approval rate
- Allotted time
- Reward
- Initial hits

Semantics (1440)

- Amount of words
- Amount of links
- Amount of images
- Unigrams
- Topics (LDA)
- Keywords

Visual (47)

- Body text percentage
- No. style files
- No. text groups
- No. Image Areas
- Emphasized body text
 %
- Colorfulness
- Color histogram

Modeling Complexity: Regression

Ground truth:

 63.78 ± 11.46

MFLR:

LR with dimension reduction

Feature Set	Regression Models			
	Linear	Lasso	MFLR	Random Forest
Metadata	13.37 ± 4.18	13.16 ± 4.24	_	9.94 ± 1.68
Visual	14.86 ± 4.01	12.50 ± 2.07	9.97 ± 1.28	10.21 ± 1.15
Content	12.87 ± 1.64	9.97 ± 1.27	9.18 ± 1.83	10.00 ± 1.47
Content LDA	10.34 ± 1.84	9.23 ± 1.44	_	11.80 ± 1.18

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Task complexity can be robustly (low std) predicted with relatively small error

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Content features with proper dimension reduction result in best performance

Visual Feature	lmp.	Semantic Features	lmp.
visualAreaCount	3.35	linkCount	2.42
hueAvg	0.09	wordCount	1.37
		keyword: audio	0.09
		keyword: transcribe	0.07
		keyword: writing	0.06
imageAreaCount	-0.27	unigram: <i>clear</i>	-0.06
colourfulness1	-0.63	unigram: <i>identify</i>	-0.07
scriptCount	-1.52	unigram: <i>date</i>	-0.09
valAvg	-1.71	keyword: <i>easy</i>	-0.10
cssCount	-1.82	imageCount	-1.01

More visual items lead to higher task complexity perceived by workers

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A better design of the task presentation (CSS) and more interactive components (JS) could decrease the complexity

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Complexity is reflected from the point of view of required actions to be performed by workers (e.g. transcribe), task type (e.g. writing), and content matter (e.g. audio).

Applying Complexity to Throughput Prediction

- Task throughput, i.e. completion rate
 - Dominated by batch size (Difallah et al. 2015)
 - Workers select tasks with many HITs to maximise reward opportunities
- Control for batch size, then apply complexity
 - Help most in the predicting the throughput of small tasks

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suggesting that complexity could help explaining the task selection strategy

Conclusions & Discussions

- We can, to some extent, measure and predict task complexity from task properties
- Can this help to:
 - Inform better task design?
 - Inform task recommendation?
 - Estimate reliability in task completion?

Thank you!

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