２０２４年度

大学院文学研究科博士課程前期２年の課程入学試験

（　夏期・一般選抜　）問題

専門科目　計算人文社会学　専攻分野

試験開始の合図があるまで、この問題冊子を開いてはいけない。

受験記号番号	

成 績	

2024年度

大学院文学研究科博士課程前期２年の課程入学試験

（夏期・一般選抜）問題

専門科目（　計算人文社会学　専攻分野）

注意）問題用紙は4枚ある．解答は5枚目から記入せよ．解答の順序は自由だが，どの問題の解答であるかが分かるように，問題番号を間違いなく記入すること．

問題 1.

次の標準形ゲームについて以下の問いに答えよ．

列プレイヤー

行プレイヤー

	W	X	Y
A	0, 0	1, 2	2, 1
B	2, 5	0, 0	3, 4
C	2, 2	5, 3	0, 4

(1)　このゲームの純戦略ナッシュ均衡となる戦略の組み合わせを全て示し，その組み合わせがナッシュ均衡であることを証明しなさい．

(2)　パレート最適の定義を述べ，このゲームにおけるパレート最適な状態を全て示せ．

（次頁に続く）

問題2.

次の表は高・雨宮（2013）によるものである．2008年に173名の大学生に対して実施された質問紙調査の回答から，在日コリアンに対する意識に対して探索的因子分析が行われた．3つの因子が抽出されており，すべての項目に単一の因子が0.4以上の負荷を示している．著者たちは第1因子を「古典的レイシズム」，第2因子を「現代的レイシズム」と命名している．

この結果を踏まえ，以下の問いに答えなさい．

(1) 一般的に探索的因子分析を行う動機としてはどのようなものが挙げられるか．

(2)「共通性」の意味と，その値が大きいことの解釈を述べなさい．

(3)「古典的レイシズム」と「現代的レイシズム」の特徴としてどのようなことが言えるか述べなさい．

	因子負荷量			共通性
	第1因子	第2因子	第3因子	
在日朝鮮人は、一般的に日本人ほど知的能力に優れていない	.82	-.17	-.21	.37
在日朝鮮人は、その場に自分がふさわしいか配慮して控えめに振る舞うべきだ	.67	-.01	.02	.46
在日朝鮮人と日本人が結婚するのは、不幸なことだ	.67	.12	-.09	.48
在日朝鮮人に隣に住まれると、自分と同程度の収入・学歴があったとしても、かなり気にかかる	.65	.08	-.09	.39
在日朝鮮人の居住の自由を認める法には、反対だ	.47	.10	.28	.56
日本国内で日本人と在日朝鮮人との法的平等を認めようとするのは、間違いだ	.40	.13	.35	.58
在日朝鮮人は、教育における差別の解消を求めると称して、不当に強い要求をしてきた	-.18	.75	.03	.43
在日朝鮮人は、平等の名の下に過剰な要求をしている	.11	.65	-.04	.51
在日朝鮮人たちはすでに、不当に高い経済的地位を得ている	.18	.55	-.13	.39
持ち主が在日朝鮮人には家屋を提供したいと思っていないときでも在日朝鮮人が家屋を借りたり買ったりできるようにするための法には、賛成である	.07	.03	.71	.60
一般的にいって、異民族・人種の完全な統合が望ましい	.05	-.26	.56	.29
在日朝鮮人が現状を不満に思うのももっともだ	-.31	.10	.50	.16
固有値	4.43	1.45	1.13	
回転後の負荷量平方和	3.65	2.78	2.47	

作題者注：論文中では「在日コリアン」という表現が使用されているが，これは一般には必ずしも浸透していないと著者らは考え，質問紙では「在日朝鮮人」という表現が使用されている．

(出典) 高史明・雨宮有里，2013,「在日コリアンに対する古典的／現代的レイシズムについての基礎的検討」『社会心理学研究』28(2): 67-76.

(次頁に続く)

問題3. 次の語句について，1語句につき100字程度で簡潔に説明せよ.

①自然言語処理 ②スクレイピング

問題4. 以下の英文を読み，問いに答えなさい.

(1) 下線部 (a) を日本語に訳しなさい.

(2) 下線部 (b) を日本語に訳しなさい.

(3) 下線部 (c) について本文に即して日本語で説明しなさい.

In the past 15 years, social science has experienced the beginnings of a 'computational revolution' that is still unfolding. In part this revolution has been driven by the technological revolution of the internet, which has effectively digitized the social, economic, political, and cultural activities of billions of people, generating vast repositories of digital data as a byproduct. And in part it has been driven by an influx of methods and practices from computer science that were needed to deal with new classes of data—such as search and social media data—that have tended to be noisier, more unstructured, and less 'designed' than traditional social science data (for example, surveys and lab experiments). One obvious and important outcome of these dual processes has been the emergence of a new field, now called computational social science, that has generated considerable interest among social scientists and computer scientists alike.

What we argue in this paper, however, is that another outcome—less obvious but potentially even more important—has been the surfacing of a tension between the epistemic values of social and computer scientists. On the one hand, social scientists have traditionally prioritized the formulation of interpretatively satisfying explanations of individual and collective human behaviour, often invoking causal mechanisms derived from substantive theory. On the other hand, computer scientists have traditionally been more concerned with developing accurate predictive models, whether or not they correspond to causal mechanisms or are even interpretable.

In turn, these different values have led social and computer scientists to prefer different methods from one another, and to invoke different standards of evidence. For example, (a) <u>whereas quantitative methods in social science are designed to identify causal relationships or to obtain unbiased estimates of theoretically interesting parameters, machine learning methods are typically designed to minimize total error on as-yet unseen data.</u> As a result, it is standard practice for social scientists to fit their models entirely 'in-sample', on the grounds that they are seeking to explain social processes and not to predict outcomes, whereas for computer scientists evaluation on 'held out' data is considered obligatory. Conversely, computer scientists often allow model complexity to increase as long as it continues to improve predictive performance, whereas for social scientists models should be grounded in, and therefore constrained by, substantive theory.

We emphasize that both approaches are defensible on their own terms, and both have generated large, productive scientific literatures; however, both approaches have also been subjected to serious criticism. On the one hand, (b) <u>theory-driven empirical social science has been criticized for generating findings that fail to replicate, fail to generalize, fail to predict outcomes of interest, and fail to offer solutions to real-world problems.</u> On the other hand, complex predictive models have also been criticized for failing to generalize as well as being uninterpretable and biased. Meanwhile, extravagant claims that the ability to mine sufficiently large datasets will result in an 'end of theory' have been widely panned. How might we continue to benefit from the decades of thinking and methodological development that have been invested in these two canonical traditions while also acknowledging the legitimacy of these criticisms? Relatedly, how might social and computer scientists constructively reconcile their distinct epistemic values to produce new methods and standards of evidence that both can agree are desirable?

(次頁に続く)

(c) Our position is that each tradition, while continuing to advance its own goals, can benefit from taking seriously the goals of the other. Specifically, we make two related contributions. First, we argue that while the goals of prediction and explanation appear distinct in the abstract they can easily be conflated in practice, leading to confusion about what any particular method can accomplish. We introduce a conceptual framework for categorizing empirical methods in terms of their relative emphasis on prediction and explanation. In addition to clarifying the distinction between predictive and explanatory modelling, this framework reveals a currently rare class of methods that integrate the two. Second, we offer a series of suggestions that we hope will lead to more of what we call integrative modelling. In addition, we advocate for clearer labelling of the explanatory and predictive power of individual contributions and argue that open science practices should be standardized between the computational and social sciences. In summary, we conclude that while exclusively explanatory or predictive approaches can and do contribute to our understanding of a phenomenon, claims to have understood that phenomenon should be evaluated in terms of both. Considering the predictive power of explanatory models can help to prioritize the causal effects we investigate and quantify how much they actually explain, and may reveal limits to our understanding of phenomena. Conversely, an eye towards explanation can focus our attention on the prediction problems that matter most and encourage us to build more robust models that generalize better under interventions and changes. Taking both explanation and prediction seriously will therefore be likely to require researchers to embrace epistemic modesty, but will advance work at the intersection of the computational and social sciences.

（出典） Hofman, J.M., Watts, D.J., Athey, S. et al. 2021 "Integrating explanation and prediction in computational social science" *Nature* 595, 181–188.

受験記号番号	

受験記号番号	