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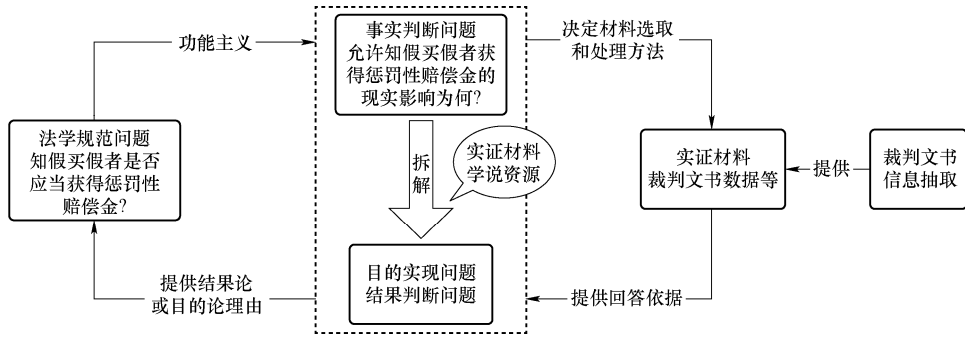
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Theodore Eisenberg, , 450 Journal of the American Statistical Association 665, 665(2000).



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34 George L. Priest & Benjamin Klein, , 13 *The Journal of Legal Studies* 1, 14–37 (1984).
Eric Helland, Daniel Klerman & Yoon-Ho A. Lee, , 174 *Journal of Institutional and Theoretical Economics* 143, 143–170 2018 .
Jonah B. Gelbach, , 174 *Journal of Institutional and Theoretical Economics* 171, 171–176 2018 .

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128–133

36 Benjamin L. Liebman et al., , 8 *Journal of Law and Courts* 177, 185–190 2020 .
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			Association for Computational Linguistics: ACL 2022, 188 (2022).			
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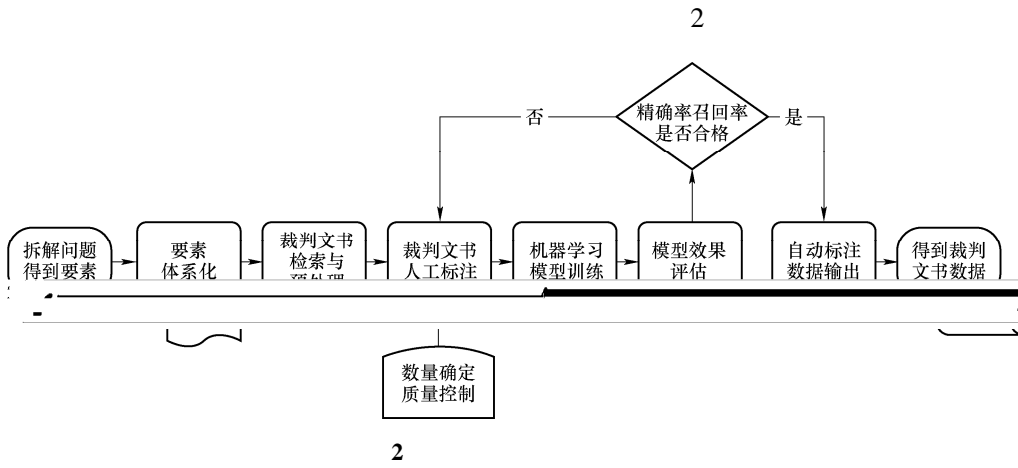
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, Findings of the Association for Computational

Linguistics: ACL 2022, 189 (2022).

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, Findings of the Association for Computational Linguistics: ACL

2022, 187 (2022).

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83 Artstein R, in Nancy Ide & James Pustejovsky eds., Handbook of Linguistic Annotation, Dordrecht Springer, 2017, p. 297–313.

84 2021 3 121

85 Feng Yao et al., Findings of the Association for Computational Linguistics: ACL 2022, 188 (2022).

86 2016 23–27

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		1 Positive		0 Negative	
1 Positive		TP True Positive		FN False Negative	
0 Negative		FP False Positive		TN True Negative	

Precision

Recall

F_1 score

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$$\begin{aligned}
 &= \frac{TP}{TP + FP} \\
 &= \frac{1}{1 + 1} \\
 F_1 &= \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}
 \end{aligned}$$

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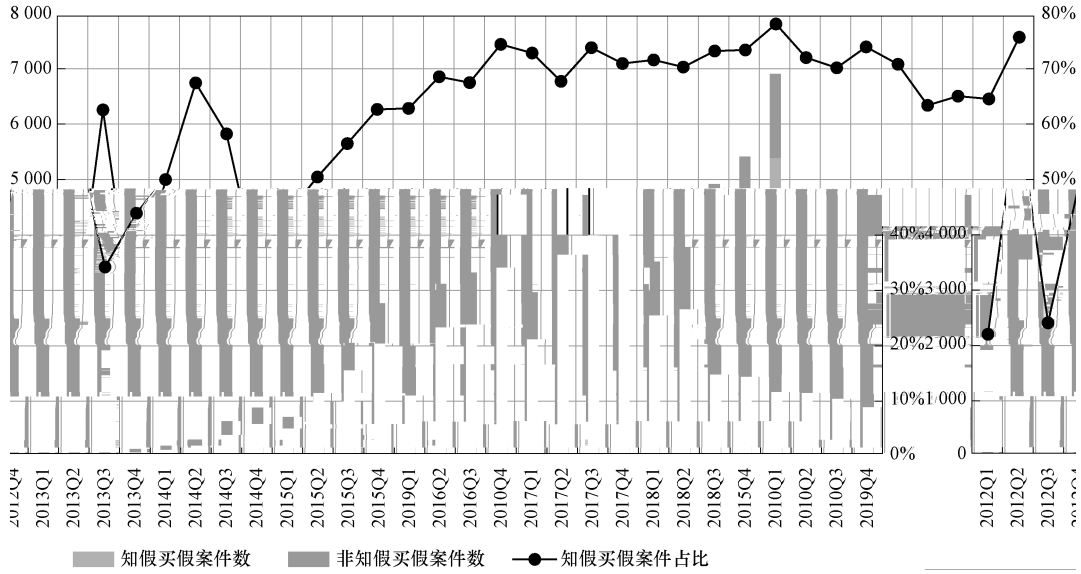
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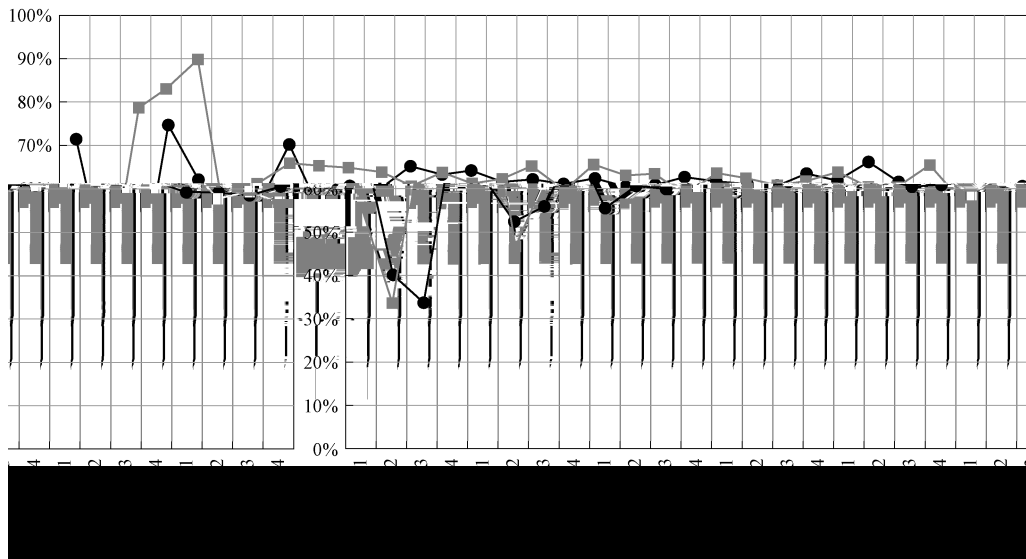
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The Empirical Legal Research Method Based on Judgement Data

—An Example from Intentional Purchasing of Defective Products

XIONG Bingwan WANG Junle

Abstract: Taking intentional purchasing of defective products as an example, this article comments on the empirical legal research method, through analyzing data extracted from judgments of punitive damages. Empirical legal research is a complete cycle, starting from normative jurisprudential problems, guided by teleology or consequentialism, deconstructing questions or concepts with problem orientation, theoretical resource and empirical evidence. It connects the legal problem with empirical information, and in turn analyzes facts better using empirical material, with the purpose of resolving relevant legal problems. Judgements are essential empirical materials. When conducting empirical researches with a large number of judgements, information can be extracted with precision from the original judgments via technologies like machine learning. At the same time, it should be noted that judgments are important yet limited representations of the legal practice activities, and it is necessary to work cautiously when using judgements for data analysis in empirical research, by assessing the validity of data rigorously and taking alternatives flexibly. Just like other field of scientific inquiry, empirical legal research does not offer a conclusive determination of the empirical world. It pursues an interpretation with higher probability and develops continuously with an open attitude.

Keywords: Empirical Research; Judgments; Information Extraction; Punitive Damages; Intentional Purchasing of Defective Products