Research Seminar in Data Science
Review of a conference paper

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1 Causal Inference in Time Series via Supervised Learning

1.1 Summary (not part of the review paper template)

1.2 Topics to look up (not part of the review paper template)

- i.i.d. data = Independent and identically distributed random variables
  - *In probability theory and statistics, a sequence or other collection of random variables is independent and identically distributed (i.i.d. or iid or IID) if each random variable has the same probability distribution as the others and all are mutually independent.*
- Granger causality
  - Useful info.
- Similar research to causal inference in time series
  - Useful info.
- Kernel Mean Embedding
  - Useful info.
- Reproducing Kernel Hilbert Space (RKHS)
  - Useful info.
- Maximum Mean discrepancy (MMD): See Paper "A kernel method for the two-sample problem"
  - Useful info.
- Traditional methods for identifying granger causality: Regression models such as vector autoregressive model (VAR) nad the Generalized Additive Model (GAM)
- Kernel Kalman Filter
- Conditional Embedding Operator (KKF-CEO)

1.3 Relevance

(a) Is the paper fully withing the scope of the conference?

- **Answer:** The "Call for papers"-section on the website of the 27th International Joint Conference on Artificial Intelligence and the 23rd European Conference on Artificial Intelligence `https://www.ijcai-18.org/cfp/` states that *"IJCAI-ECAI 2018 welcomes submissions across all areas of AI. The conference scope includes all subareas of AI, including (but not limited to) traditional topics such as machine learning, search, planning, knowledge representation, reasoning, constraint satisfaction, natural language processing, robotics and perception, and multiagent* *systems. We expressly encourage work that cuts across technical areas and/or integrated capabilities. We encourage all types of contributions including theoretical, engineering and applied. We also encourage papers on AI techniques in the context of novel application domains, such as security, sustainability, health care, transportation, and commerce."* Based on this description and the topic of the paper which is about using supervised (machine) learning techniques in order to do causal inference in time series, I would say that this paper fully fits into the scope of the conference.

(b) Will the questions and results of the paper be of interest to researchers in the field?

- **Answer:** Given the fact that there does not seem to be a lot of prior research and solutions addressing the same problem of treating causal inference in time series as a classification problem, I would assume that this paper is of high interest.

(c) Did the authors ignore (or appear unaware of) highly relevant prior work?

- **Answer:** The paper "Supervised Estimation of Granger-Based Causality between Time Series" Benozzo et al. (2017) seems to be highly relevant but was not cited. The paper "Parametric and non-parametric criteria for causal inference from time-series" Chicharro (2014) seems relevant but was not cited.

(d) Is previous work in the area of the paper properly cited?

- **Answer:** Previous work has been briefly mentioned in one sentence in secion "1 - Introduction" by stating that there has been prior work which uses classification to infer causal relationships from i.i.d. data. The mentioned sources are namely:

  I A paper called "From dependency to causality: a machine learning approach" Bontempi and Flauder (2015). According to google scholar it has been cited only 3 times.

  II A Kaggle competition called "Cause-effect pairs" which can be found at `https://www.kaggle.com/c/cause-effect-pairs`. Instead of just citing the Kaggle competition, it would be better to cite the published papers or code repositories of the winners of the competition. Otherwise the reader has to browse though the Kaggle forum to find the actual results. The first three winners published their code in the following Github repositories:
  - Team ProtoML `https://github.com/diogo149/CauseEffectPairsChallenge`
  - Team jarfo `https://github.com/jarfo/cause-effect`
  - Team FirfiD `https://github.com/ssamot/causality`

  III A paper called "Towards a learning theory of cause-effect inference" Lopez-Paz et al. (2015). According to google scholar it has been cited 47 times.

  IV A paper called "Discovering causal signals in images" Lopez-Paz et al. (2017). According to google scholar it has been cited 13 times.

  In section "4 - Related Work", it is mentioned that Lopez-Paz et al. (2015) is also using a supervised learning method for i.i.d. data called "Randomized Causation Coefficient (RCC)" which is using kernel mean embedding to obtain features. One sentence is dedicated to describe the difference between the work of Lopez-Paz et al. (2015) and the proposed approach. Previous work has been cited properly but is sparse. In my opinion the citation to the Kaggle competition needs improvement in terms of adding details to the winning solutions.

1.4 Significance

(a) Is this a significant advance in the state of the art?

- **Answer:** I would say it is not a significant advance. I also miss the statement that this approach would beat the state-of-the-art approach in the conclusion.

(b) Is this a paper that people are likely to read and cite?

- **Answer:** Because this paper is addressing a very specific topic where not alot of prior research has been done, I would assume that people are likely to read and cite this paper.

(c) Does the paper address an important problem?

- **Answer:** I would assume that this paper addresses a problem which is not important to most researchers in the machine learning and artificial intelligence domain.

(d) Does it open new research directions?

- **Answer:** Yes, it would be interesting to see how other classifiers perform on the presented features.

(e) Is it a paper that is likely to have a lasting impact?

- **Answer:** Given that the last paper which seems to cover the same research domain is already three years old I would assume that this paper has a lasting impact.

1.5 Originality

- Reviewers should recognise and reward papers that propose genuinely new ideas. As a reviewer you should try to assess whether the ideas are truly new. Novel combinations, adaptations or extensions of existing ideas are also valuable.
  - **Answer:** The only thing which seems to make this paper different from the work of Lopez-Paz et al. (2015) is the feauture engineering part although this part seems to be sophisticated.

1.6 Technical Quality

(a) Are the results technically sound?

- **Answer:** I am not an expert in this domain so it is hard to tell. The results seem to be technically correct.

(b) Are there obvious flaws in the conceptual approach?

- **Answer:** I could not find flaws regarding the conceptual approach.

(c) Are claims well-supported by theoretical analysis or experimental results?

- **Answer:** Yes.

(d) Are the experiments well thought out and convincing?

- **Answer:** The synthetic time series (linear and nonlinear) seem to be a good choice for the experiment and seem to be convincing.

(e) Will it be possible for other researchers to replicate these results?

- **Answer:** The technical detail should be sufficient to replicate the results.

(f) Is the evaluation appropriate?

- **Answer:** The evaluation is based on comparing the proposed method with the state-of-the-art approach "RCC" and granger causality methods, namely the Vector Autoregressive Model, Generative Additive model and the kernel regression. The macro and micro-averaged F1-score is used as the evaluation metric. The evaluation seems appropriate.

(g) Did the authors clearly assess both the strenghts and weaknesses of their approach?

- **Answer:** The authors state that their approach also works with n-variate time series where n > 3 but in reality it is restricted to trivariate time series. This is a bit misleading. Besides that, I could not find any further notes about the weaknesses of the approach.

1.7 Clarity and quality of writing

(a) Is the paper clearly written?

- **Answer:** Yes.

(b) Is there a good use of examples and figures?

- **Answer:** Yes, the usage of examples and figures seems sufficient to me.

(c) Is it well organized?

- **Answer:** The overall structure seems fine to me although I am missing a separated discussion section. I am not sure if the overall structure has been dictated by the conference.

(d) Are there problems with style and grammar?

- **Answer:** I could not find any style or grammar mistakes.

(e) Are these issues with typos, formatting, references, etc.?

- **Answer:** The only issue with regards to references has already been described in section "Relevance", point d) when it comes to referencing a Kaggle competition website.

1.8 Scholarship

(a) Does the paper situate the work with respect to the state of the art?

- **Answer:** Given that Lopez-Paz et al. (2015) is the state-of-the-art, the paper situates the work with respect to the before mentioned paper in a sufficient way. The experiments were chosen in a direct comparison towards Randomized Causation Coefficient.

(b) Are relevant papers cited, discussed, and compared to the presented work?

- **Answer:** Same remark as above although I would question the statement that Lopez-Paz et al. (2015) is the only work which can be used as a direct comparison in the experiments. Furthermore, the related work section seems to be a bit sparse to me. I expected more explicit statements in how far this paper is novel to the other approach. At its core, is there just a difference in the chosen features?

1.9 Overall Score

- 10 - This is best-paper material
- 9 - An excellent paper, a very strong accept
- 8 - A very good paper, a strong accept
- 7 - A good paper, accept
- **6 - A good paper overall. I vote for acceptance, although would not be upset if it were rejected because of the low acceptance rate**
- 5 - Decent paper, but may be below the IJCAI threshold. I tend to vote for rejecting it, although would not be upset if it were accepted.
- 4 - I vote for rejecting it, but could be persuaded otherwise.
- 3 - A weak paper, just not good enough.
- 2 - A clear rejection. I vote and argue for rejection. Clearly below the standards of the conference.
- 1 - A very strong rejection. I will actively fight for rejection.

1.10 Confidence on your assessment

- 10 - My own current research is on the topic of the paper
- 9 - I have undertaken research on the topic of the paper
- 8 - I am an expert in this area
- 7 - I have up-to-date knowledge in the area
- 6 - I don't have complete knowledge of the area, but can assess the value of the work
- 5 - I have a general understanding of the area
- **4 - My assessment is an informed guess**
- 3 - My knowledge in the area is limited
- 2 - My knowledge in the area is very limited
- 1 - My assessment can be wrong

2 Main Review

2.1 Comments to Authors. (free text)

- Main body of the review. Make sure you substantiate all the scores for the different criteria above, and refer to the descriptions given.
- Give informative content
- Be constructive
- Write your comments in the same way you would like to receive comments on your own papers.
- Include page/line numbers when referring to specific parts.
- Add a separate "minor details" section for e.g. (con)textual and/or typographical issues.

2.2 Confidential Comments (Not visible to the authors, only to other reviewers/program char)

if applicable

References

Benozzo, D., Olivetti, E., and Avesani, P. (2017). Supervised estimation of granger-based causality between time series. *Frontiers in neuroinformatics*, 11.

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Lopez-Paz, D., Muandet, K., Schölkopf, B., and Tolstikhin, I. (2015). Towards a learning theory of cause-effect inference. In *International Conference on Machine Learning*, pages 1452–1461.

Lopez-Paz, D., Nishihara, R., Chintala, S., Schölkopf, B., and Bottou, L. (2017). Discovering causal signals in images. In *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR 2017)*.