Methods of scientific research exercise 4 – paper review

The exercise consists of writing an 800-word review of one of twenty papers that are suggested. These papers are all on computer science and have appeared in the prestigious general science journal *Proceedings of the National Academy of Sciences of the United States of America* (PNAS). Each is around 6–8 pages.
Your review should pay attention to the issues reviewed in the lecture, and should give suggestions to improve the paper (from a computer science perspective).

Please go to
https://ai.vub.ac.be/~bart/reviewnumbers.html
type in your student number in order to convert it to paper numbers. Choose one of these three papers to do your review. References are found on Canvas. All papers are accessible through the VUB library system or are open access.

A good review

- Contains the reference of the paper
- Contains answers to the closed questions mentioned in the slides (using Likert scale-like answers, for instance "very good", "good", "average", "bad", "very bad")
- Summarizes the papers very briefly
  - Not paraphrasing the paper's abstract, but stating what the reviewer learnt from the paper
- Gives a brief opinion about the paper
- Explains the basis for this opinion
- Gives suggestions how to improve the paper
  - Both for content and form
  - But importantly: engage with the content; use your expertise as a computer scientist
- Do not forget to put your name and student number on the assignment!
- And use the usual filename: firstnameLASTNAME_MWO4.pdf
- Check the slides (of the whole course) for more information!

The deadline is January 20, midnight.

Paper list

1. Bouchard-Côté, A., Hall, D., Griffiths, T. L., & Klein, D. (2013) Automated reconstruction of ancient languages using probabilistic models of sound change *PNAS 110 (11)* 4224-4229
2. Dandekar, P., Goel, A., & and Lee, D. T. (2013) Biased assimilation, homophily, and the dynamics of polarization *PNAS* 110 *(15) 5791-5796*
3. Gopalan P. K., & and Blei, D. M. (2013) Efficient discovery of overlapping communities in massive networks, PNAS 110(36) 14534-14539
4. Rutherford, A., Cebrian, M., Dsouza, S., Moro, E., Pentland, A., & Rahwan, I. (2013) Limits of social mobilization *PNAS 110 (16) 6281-6286*
5. Gavaldà-Miralles, A., Choffnes, D. R, Otto, J. S., Sánchez, M. A., Bustamante, F. E., Amaral, L.A. N., Duch, J., & Guimerà, R. (2014) Impact of heterogeneity and socioeconomic factors on individual behavior in decentralized sharing ecosystems *PNAS* 111 *(43) 15322-15327*
6. Santi, P., Resta, G., Szell, M., Sobolevsky, S., Strogatz, S. H., & Ratti, C. (2014) Quantifying the benefits of vehicle pooling with shareability networks *PNAS 2014* 111 *(37) 13576-13581*
7. Zhang, P. & Moore, C. (2014) Scalable detection of statistically significant communities and hierarchies, using message passing for modularity *PNAS 111 (51)* 18144-18149
8. Dera, R. and Martius, G. (2015) Novel plasticity rule can explain the development of sensorimotor intelligence *PNAS 112 (45)* E6224-E6232
9. Geman, D., Geman, S., Hallonquista, N. & Younes, L. (2015) Visual Turing test for computer vision systems *PNAS 112(12)* 3618-3623
10. Ibsen-Jensen, R., Chatterjee, K., & Nowak, M. A. (2015) *PNAS 112 (51)* 15636-15641. https://doi.org/10.1073/pnas.1511366112 1-6
11. Baldassi, C., Borgs, C., Chayes, J. T., Ingrosso, A., Lucibello, C., Saglietti, L., & Zecchina, R. (2016) Unreasonable effectiveness of learning neural networks: From accessible states and robust ensembles to basic algorithmic schemes *PNAS 113 (48) E7655-E7662.* https://doi.org/10.1073/pnas.1608103113
12. Esser, S. K., Merolla, P. A., Arthur, J. V., Cassidy, A. S., Appuswamy, R., Andreopoulos, A., Berg, D. J., McKinstry, J. L., Melano, T., Barch, D. R., di Nolfo, C., Datta, P., Amir, A., Taba, B., Flickner, M. D., & Modha D. S. (2016) Convolutional networks for fast, energy-efficient neuromorphic computing *PNAS 113 (41) 11441-11446*. https://doi.org/10.1073/pnas.1604850113
13. Zander, T. O., Krol, L. R., Birbaumer, N. P. & Gramann, K. (2016) Neuroadaptive technology enables implicit cursor control based on medial prefrontal cortex activity *PNAS 113 (52)* 14898-14903. https://doi.org/10.1073/pnas.1605155114
14. Mayer, J., Mutchler, P., & Mitchell, J. C. (2016). Evaluating the privacy properties of telephone metadata. *Proceedings of the National Academy of Sciences*, *113*(20), 5536–5541. https://doi.org/10.1073/pnas.1508081113
15. Gebru, T., Krause, J., Wang, Y., Chen, D., Deng, J., Aiden, E. L., & Fei-Fei, L. (2017). Using deep learning and Google Street View to estimate the demographic makeup of neighborhoods across the United States. *Proceedings of the National Academy of Sciences*. https://doi.org/10.1073/pnas.1700035114
16. Lokhov, A. Y., & Saad, D. (2017). Optimal deployment of resources for maximizing impact in spreading processes. *Proceedings of the National Academy of Sciences*, *114*(39), E8138–E8146. https://doi.org/10.1073/pnas.1614694114
17. Musco, C., Su, H.-H., & Lynch, N. A. (2017). Ant-inspired density estimation via random walks. *Proceedings of the National Academy of Sciences*, *114*(40), 10534–10541. https://doi.org/10.1073/pnas.1706439114
18. Pokhriyal, N., & Jacques, D. C. (2017). Combining disparate data sources for improved poverty prediction and mapping. *Proceedings of the National Academy of Sciences*, *114*(46), E9783–E9792. https://doi.org/10.1073/pnas.1700319114
19. Shah, S. A., & Koltun, V. (2017). Robust continuous clustering. *Proceedings of the National Academy of Sciences*, *114*(37), 9814–9819. https://doi.org/10.1073/pnas.1700770114
20. Wadhwa, N., Chen, J. G., Sellon, J. B., Wei, D., Rubinstein, M., Ghaffari, R., … Freeman, W. T. (2017). Motion microscopy for visualizing and quantifying small motions. *Proceedings of the National Academy of Sciences*, *114*(44), 11639–11644. https://doi.org/10.1073/pnas.1703715114
21. Schwarting, W., Pierson, A., Alonso-Mora, J., Karaman, S. & Rus, D. (2019) Social behavior for autonomous vehicles. *Proceedings of the National Academy of Sciences* 201820676 doi:10.1073/pnas.1820676116.