Potential topics for a computational model or grant proposal

- Predictive processing. Predictive processing or predictive coding is a theory which emphasizes that the brain is in the business of making predictions. What are the neural underpinnings of this theory and how can we probe these?
    - References:
        - Andy Clarke book, Surfing Uncertainty nicely addresses predictive processing
        - Chalasani, R., & Principe, J. C. (2013). Deep predictive coding networks. arXiv preprint arXiv:1301.3541.
        - Huang, Y., Rao, R.P.N., 2011. Predictive coding. WIRES Cogn. Sci. 2, 580–593.

- Sparse coding: Sparse coding basically shows how neuronal receptive fields can be learnt in an unsupervised manner using a sparseness assumption. This was an important computational model which explained simple receptive field properties. However, at the same time, we don't know how to characterize most neurons even in V1
    - References:
        - Olshausen, B.A., Field, D.J., 1996. Emergence of simple-cell receptive field properties by learning a sparse code for natural images. Nature 381, 607–609. doi:10.1038/381607a0
        - Olshausen, B.A., Field, D.J., 2004. What is the other 85 % of V1 doing ? 1–27.

- Gradients in the brain: Recently, a number of different representational gradients have been discovered in the brain. One example is a gradient of complexity along the ventral visual stream (Guclu & van Gerven, 2015). Another example is a gradient of numerosity in parietal cortex (Harvey et al., 2013). It remains unclear to what extent this is a general organisational principle of the brain.
    - References:
        - Guclu, U., & van Gerven, M. A. J. (2015). Deep Neural Networks Reveal a Gradient in the Complexity of Neural Representations across the Ventral Stream. *Journal of Neuroscience*, *35*(27), 10005–10014. http://doi.org/10.1523/JNEUROSCI.5023-14.2015
        - Harvey, B. M., Klein, B. P., Petridou, N., Dumoulin, S. O., Brannon, E. M., Terrace, H. S., … Dumoulin, S. O. (2013). Topographic representation of numerosity in the human parietal cortex. *Science (New York, N.Y.)*, *341*(6150), 1123–6. http://doi.org/10.1126/science.1239052

- Organisation of conceptual representations: how are concepts represented in the brain? Is very concept coded in a single neuron or do we have distributed representations? Is conceptual information only coded in the temporal cortex or are other brain areas also involved? Recently, computational methods have been used to try to answer these questions, but much still remains unclear.

- References:
  - Huth, A. G., Nishimoto, S., Vu, A. T., & Gallant, J. L. (2012). A Continuous Semantic Space Describes the Representation of Thousands of Object and Action Categories across the Human Brain. *Neuron*, *76*(6), 1210–1224. http://doi.org/10.1016/j.neuron.2012.10.014
  - Huth, A. G., de Heer, W. A., Griffiths, T. L., Theunissen, F. E., & Gallant, J. L. (2016). Natural speech reveals the semantic maps that tile human cerebral cortex. *Nature*, *532*(7600), 453–458. http://doi.org/10.1038/nature17637

- Active sensing: The brain is not just a passive observer, but is able to act in order to shape the next sensory input. How does the brain choose its actions in order to perform fast perceptual inference.
  - References
    - Yang, S. C. H., Lengyel, M., & Wolpert, D. M. (2016). Active sensing in the categorization of visual patterns. Elife, 5, e12215.

- Neural implementation of reinforcement learning: The brain ultimately needs to learn to generate optimal actions e.g. via reinforcement learning. What would neurally plausible versions of reinforcement learning look like? What is the role of neuromodulation?
  - References
    - Miconi, T., 2016. Flexible decision - making in recurrent neural networks trained with a biologically plausible rule 1–38. doi:10.1101/057729

- The value of information in an uncertain world: The brain needs to weigh the outcome of previous decisions according to their importance for predicting future outcomes. Does the brain act according to a bayes theorem in this situation?
  - References
    - Behrens, T. E., Woolrich, M. W., Walton, M. E., & Rushworth, M. F. (2007). Learning the value of information in an uncertain world. *Nature neuroscience*,*10*(9), 1214-1221.

- Probabilistic inference in neural networks: How does the brain deal with uncertainty in the world? People behave in many situations as Bayesian observer, but how can neurons give rise to this behavior?
  - References
    - Orhan, A. E., & Ma, W. J. (2016). The Inevitability of Probability: Probabilistic Inference in Generic Neural Networks Trained with Non-Probabilistic Feedback.arXiv preprint arXiv:1601.03060.

- Integrated information theory of consciousness: For decades neuroscientists and philosophers have been trying to come up with a theory to explain how consciousness arises from the brain. Tononi's integrated theory of consciousness has gained a lot of attention in recent years. It basically states that consciousness is the same as integrated information. However, there is still little experimental evidence to support this theory

- References:
  - Tononi, G. (2008). Consciousness as integrated information: a provisional manifesto. *The Biological Bulletin*, *215*(3), 216–42. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/19098144
  - Tononi, G., Koch, C., Koch, C., Baars, B., Gage, N., Dehaene, S., … Koch, C. (2015). Consciousness: here, there and everywhere? *Philosophical Transactions of the Royal Society of London. Series B, Biological Sciences*, *370*(1668), 200–227. http://doi.org/10.1098/rstb.2014.0167

- Top of the visual hierarchy: for decades it has been known that there is a processing hierarchy in the visual stream from simple features like lines with different orientations in V1 to object categories in temporal cortex (Kravtiz et al., 2013). However, what exactly is the top of the visual hierarchy? Does processing end in 'grandmother cells', in which one concept is represented by one neuron? Or is the top the motor system in the sense that sensory input is only relevant for the actions it causes?
  - References:
    - Barlow, H. (2009). Grandmother Cells, Symmetry, and Invariance: How the Term Arose and What the Facts Suggest. *The Cognitive Neurosciences*.
    - Kravitz, D. J., Saleem, K. S., Baker, C. I., Ungerleider, L. G., & Mishkin, M. (2013). The ventral visual pathway: An expanded neural framework for the processing of object quality. *Trends in Cognitive Sciences*. http://doi.org/10.1016/j.tics.2012.10.011

- Perception without visual input: sometimes we see things that are not there. This happens in pathologies when people have hallucinations, but also in healthy people. Think for example about visual illusions, filling in of the blind spot of the retina, visual imagery and dreaming. Much is still unknown about how this top-down visual experience is created. To what extent are the neural representations in visual cortex similar to actual perception? And in a more computational context, how are these top-down processes implemented?
  - References:
    - Lee, S.-H., Kravitz, D. J., & Baker, C. I. (2012). Disentangling visual imagery and perception of real-world objects. *NeuroImage*, *59*(4), 4064–73. http://doi.org/10.1016/j.neuroimage.2011.10.055

- How organisms learn to behave: Various theories have been developed that try to explain why organisms behave the way they do. There are various approaches like empowerment, causal entropic forces and free energy. Do these theories make sense?
  - References:

- Polani, D., Empowerment and State-dependent Noise - An Intrinsic Motivation for Avoiding Unpredictable Agents. mitpress.mit.edu.
- Wissner-Gross, A.D., Freer, C.E., 2013. Causal Entropic Forces. Phys. Rev. Lett. 110, 168702.
- Friston, K.J., 2010. The free-energy principle: a unified brain theory? Nat. Rev. Neurosci. 11, 127–138.

- Conceptual spaces: New language modeling approaches learn language representations that carry semantic meaning so we can perform arithmetic such as King – Man + Woman = Queen. What is the mathematical structure of these spaces?
  - References:
    - Pennington, J., Socher, R., Manning, C.D., 2014. Glove: Global Vectors for Word Representation. Proc. 2014 Conf. Empir. Methods Nat. Lang. Process. 1532–1543. doi:10.3115/v1/D14-1162
    - Mikolov, T., Sutskever, I., Chen, K., Corrado, G., Dean, J., 2013. Distributed representations of words and phrases and their compositionality. ArXiv Prepr.