SOTA GPRs for neural data

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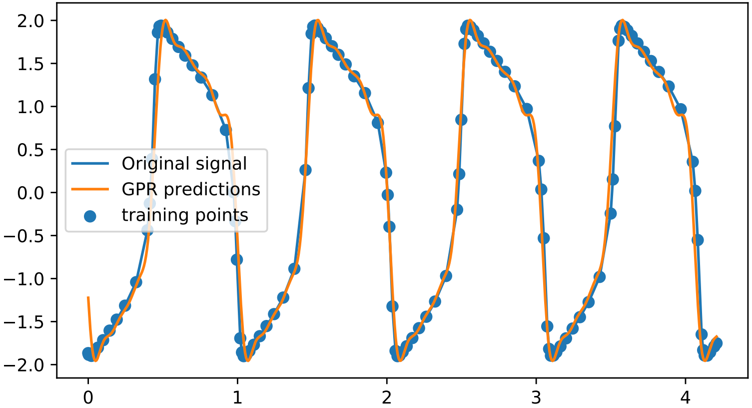
Goals

- Redraft the continuation paper
  - Week 1
- Implement and test some GP schemes
  - Week 2

My SEKernel



Reasonable fit, but fixed lengthscales means it struggles at timescale changes.
Good baseline. Bad for real neurons.

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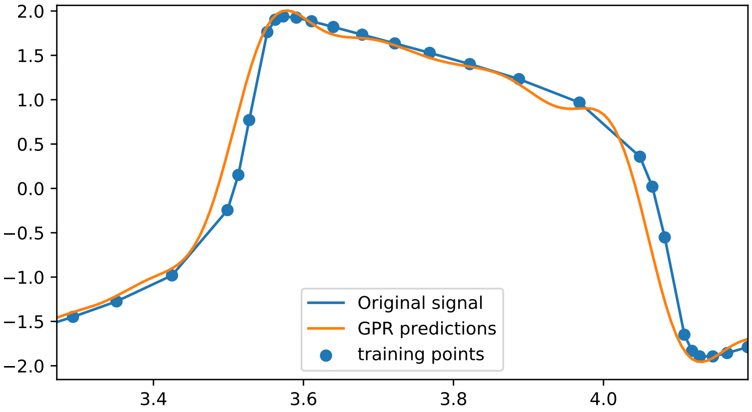

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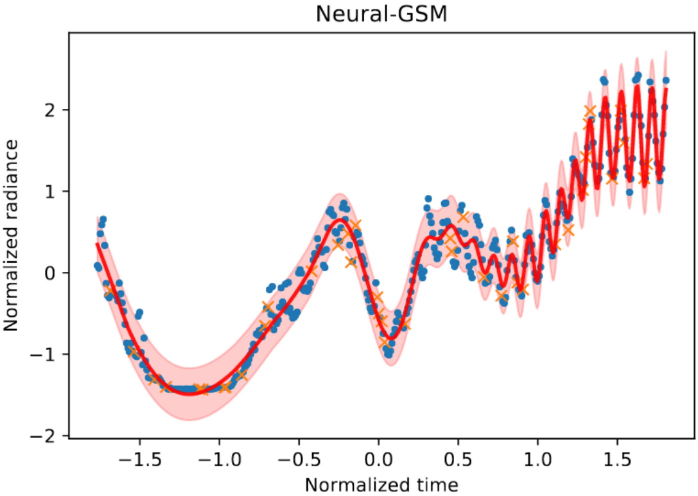
Generalised nonstationary spectral kernels

- Method identified in the literature review as being applicable to neuron data
- Fits into a sparse GP framework – good for experiments
- Models nonstationarity – varying length scales, function variance
  - Lengthscales quantify local similarity (think: wiggliness)
  - Multiple timescale dynamics means wiggliness changes across the signal
- Open source code available!

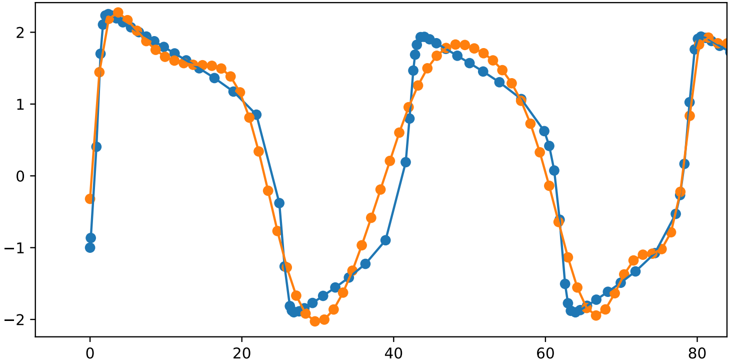
`https://github.com/sremes/nssm-gp`

Published results



Provides state-of-the-art performance on test data

My results



It does look to have varying lengthscales, but it doesn’t work well!

Possible issues

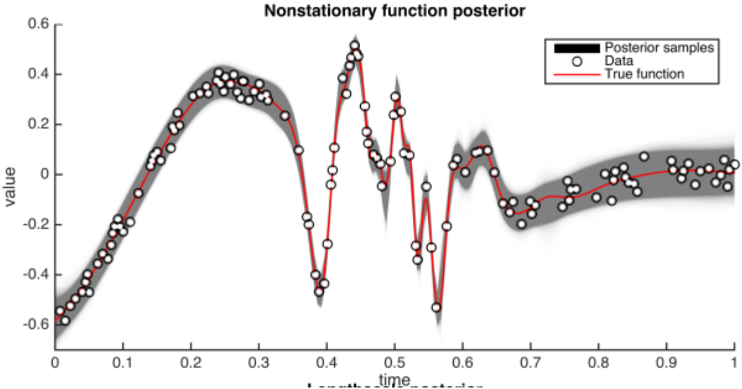
- I don't trust the code
  - Provided code relies on outdated, incompatible tensorflow, GPFlow versions; wouldn't run
  - I rewrote so it would run, but don't know tensorflow, GPFlow, so bad fit could be a code issue
- Not enough data?
- Bad training?
  - I don't know anything about the tensorflow optimizers
- Generally bad method?
  - This was tested using algos from a preprint
  - A near-identical algo was published in a conference, might work better?

Other approaches

Try other nonstationary kernels, or...

- Could use a good stationary kernel and hope its good enough
- Real neurons have very short, fast spikes. Could use one kernel for the spikes, and another for the rest
- GPFlow implements a switching kernel
  - Develop some sort of algo to detect where to switch kernels
  - Fit a switching kernel, based around these changepoints
- Could use hidden Markov chains for a piecewise model

Other nonstationary kernels



Source: Heinonen, Markus, et al. "Non-stationary gaussian process regression with hamiltonian monte carlo." Artificial Intelligence and Statistics. 2016.

Similar idea to the method I already tried, but hopefully with more usable code.

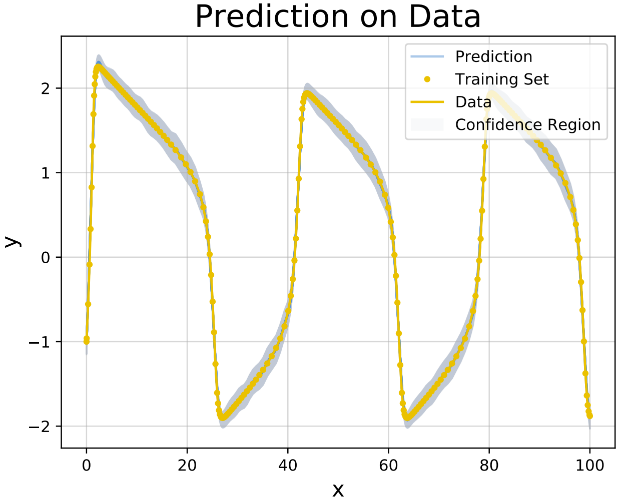
Hidden Markov chain model

- Assume there's two dynamics, $f_q(t)$ for quiescence, $f_s(t)$ for spiking
- Each dynamics are modelled as a random process
- Hidden (latent) variable θ dictates whether the neuron is spiking or quiescent
- θ follows a random process to initiate the transition from quiescence to spiking
- Model:

$$f(t,\theta) = \begin{cases} f_q(t) & \text{if } \theta = 0 \\ f_s(t) & \text{if } \theta = 1 \end{cases} \tag{1}$$

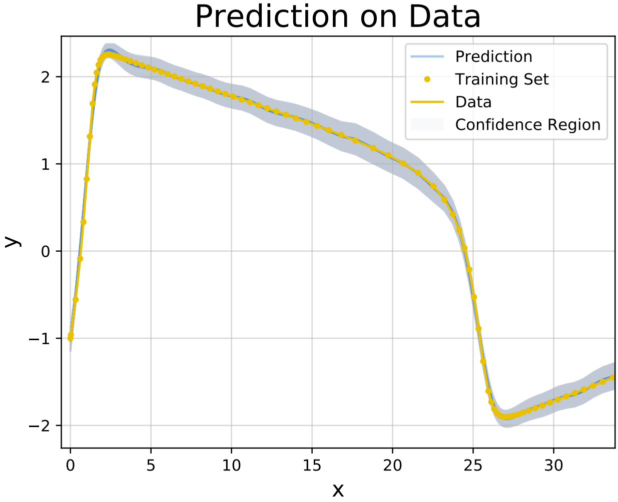
Might be easy, might be hard

Good stationary kernel



Uses the function-space distribution over kernels method; code adapted from
`https://github.com/wjmaddox/spectralgp`

Good stationary kernel



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Good stationary kernel

Caveat:

- Fitzhugh-Nagumo is slower changing than real neuron data
  - Real data would likely be strongly nonstationary, in which case this wouldn't work
- Good stationary kernels would be useful for a switching kernel, or a hidden Markov chain model
  - Have a good stationary kernel for the active phase
  - Have a good stationary kernel for the quiescent phase
  - Switch between them at the appropriate points

Good stationary kernel

Note:

- The stationary method shown here is a spectral mixture kernel – SMK
- The unsuccessful method was a generalised (nonstationary) spectral mixture kernel – GSMK
- A GSMK can model any SMK
  - Anything an SMK can model, a GSMK can model equally well
  - Reverse is not true
- Unsuccessful results are likely down to practice (coding issues), rather than theory (invalid kernel choice)

Sidenote on GPFlow

- Based on tensorflow
  - Very fast, very powerful
- Lots of the SOTA work uses GPFlow or GPyTorch
- Might be worth learning how to use it
  - Can implement and test more advanced kernels that way

Next steps

- GPs are tricky on fast-changing data; I still think they'd be useful / worth the time and effort:
  - Clean data source
  - Could allow CBC to be interfaced with existing continuation methods. . .
  - . . . or could be used to make a novel, application-specific / discretization-free continuation method
- More GPR testing
  - Try other kernels (GPFlow periodic, Heinonen Hamiltonian Monte-Carlo, switching, . . .)
  - Try to get GSM kernel to work?
  - Switching kernels?
  - Learn about Tensorflow and GPFlow?