A regime switching model for smart beta investing using hidden Markov models

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About this work

A novel dynamic asset allocation system using Feature Saliency Hidden Markov models for smart beta investing

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Abstract

The financial crisis of 2008 generated interest in more transparent, rules-based strategies for portfolio construction, with Smart beta strategies emerging as a trend among institutional investors. While they perform well in the long run, these strategies often suffer from severe short-term drawdown (peak-to-trough decline) with fluctuating performance across cycles. To address cyclicality and underperformance, we build a dynamic asset allocation system using Hidden Markov Models (HMMs). We test our system across multiple combinations of smart beta strategies and the resulting portfolios show an improvement in risk-adjusted returns, especially on more return oriented portfolios (up to 50% in excess of market annually). In addition, we propose a novel smart beta allocation system based on the Feature Saliency HMM (FSHMM) algorithm that performs feature selection simultaneously with the training of the HMM, to improve regime identification. We evaluate our systematic trading system with real life assets using MSCI indices; further, the results (up to 60% in excess of market annually) show model performance improvement with respect to portfolios built using full feature HMMs .

Keywords: Hidden Markov model, Dynamic asset allocation, Portfolio optimization, Feature Selection, Smart Beta

1. Introduction

Smart beta is a relatively new term that has become ubiquitous in asset management over the last few years. The financial theory underpinning Smart Beta, known as factor investing, has been around since the 1960s, when factors were first identified as being drivers of equity returns (Agather & Gunthorp, 2017). These factor returns can be a source of risk and/or improved return, and understanding whether any additional risk is adequately compensated with higher returns is important. (Ang, 2014).

By selecting stocks based on their factor exposures, active managers can build portfolios with particular factor exposures and so use factor investing to improve portfolio returns and/or lower risk, depending on their particular objectives. Smart beta aims to achieve these goals at a reduced cost by utilising a transparent, systematic, rules-based approach, bringing down the costs significantly when compared to active management (Asness, 2016).

While smart beta strategies have shown strong performance in the long run, they often suffer from severe short-term drawdown (peak-to-trough decline) with fluctuating performance across cycles (Arnott et al., 2016). These fluctuations can arise from extreme macroeconomic conditions, elevated volatility, heightened correlations across multiple markets and uncertainty monetary and fiscal policy responses. In this paper we address this by building a regime switching model using Hidden Markov Models (HMMs). Hidden Markov models have become one of the mainstream techniques to model times series data (Baum et al., 1970; Rabiner, 1989), with applications across many areas such as speech recognition, text classification and medical applications. We first study how a regime switching framework can be used to detect regimes across factors and, if so, add value to smart beta strategies. The prevalent approach in regime switching frameworks for asset allocation has been to specify in advance a static decision rule dependent on the predicted state (Nystrup et al., 2017a). An alternative approach is to dynamically optimise a portfolio using information from the inferred regime parameters. We follow this second approach and use the regime information to construct different types of portfolios (more return oriented and more risk focused). In a first step we build a dynamic asset allocation (DAA) system to construct portfolios through a regime switching model and perform a systematic analysis using hundreds of combinations of factors by training the HMM with the same factors that will be used for the allocation in the portfolio. Our study shows that using the regime information from the HMM has a better performance than a single regime allocation and we find that more return-oriented portfolios yield better risk-adjusted returns than their benchmarks, while the performance of more risk focused portfolios show some improvement.

Finally, the common factor in the majority of the research on regime-switching models in finance is that it considers either

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Overview

Motivation

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Two main contributions:

1. Use HMMs to identify market regimes and to build the portfolios. We did a systematic study with multiple factors and types of portfolios.
2. Use an unsupervised feature selection algorithm to select optimal features for the HMM. We show that feature selection improves regime identification.

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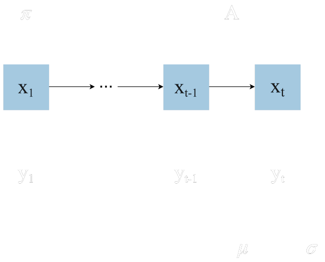

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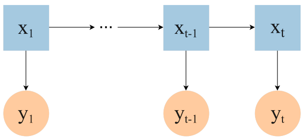

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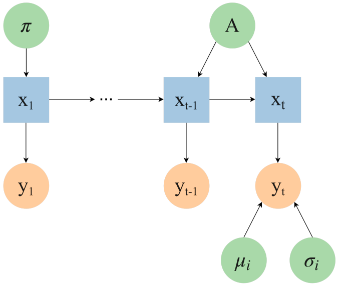

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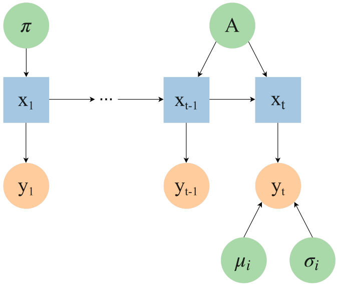

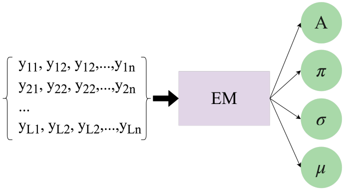

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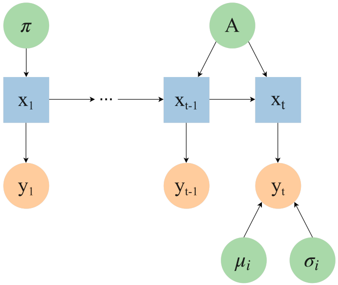

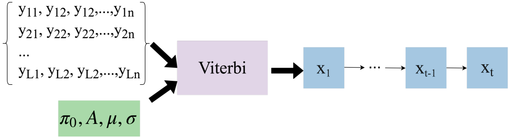

Hidden Markov Model: Example

Model

Input: 3 factor returns
Nr of states: 3
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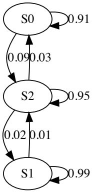

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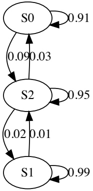

$$S0_\mu = \begin{pmatrix} 0.0015 \\ -0.0001 \\ -0.0023 \end{pmatrix} \; S1_\mu = \begin{pmatrix} 0. \\ 0.0001 \\ 0.0001 \end{pmatrix} \; S2_\mu = \begin{pmatrix} -0.0003 \\ 0.0001 \\ 0.0004 \end{pmatrix}$$

Data

Daily factor data from S&P500

The universe is ranked, a portfolio is constructed with the top 20% of stocks and short positions in the bottom 20% of stocks.

MSCI USA enhanced indices

Start from 6 MSCI indices (Value, Momentum, Size, Volatility, High Yield, Quality) and subtract equally weighted index.

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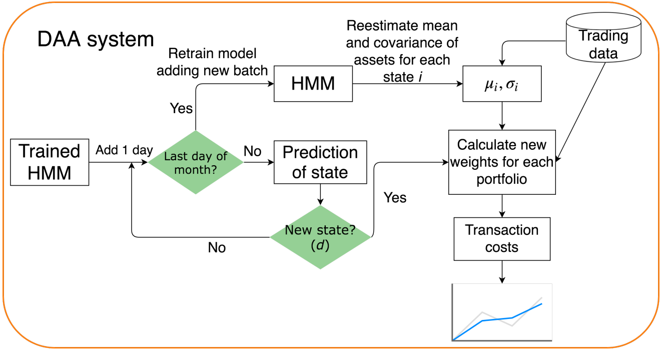
Start from 6 MSCI indices (Value, Momentum, Size, Volatility, High Yield, Quality) and subtract equally weighted index.

Dataset	Date	Nr of features	Frequency
Factor data	Jan-1988 to Feb-2016	25	Daily
MSCI Enhanced	Jan-1999 to Feb-2016	6	Daily

Dynamic Allocation System

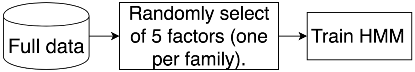
Objective: build a DAA system incorporating information from a HMM and test it systematically.

- State is determined daily, by adding one observation per day (yes, this is very noisy!).
- Given a change of state, use information from model (mean and variance) to recalculate the weights of the portfolio.
- After one month, add the observations to the stack of previous ones with an expanding window and retrain the model.



Calibration and test of DAA system

1 Training



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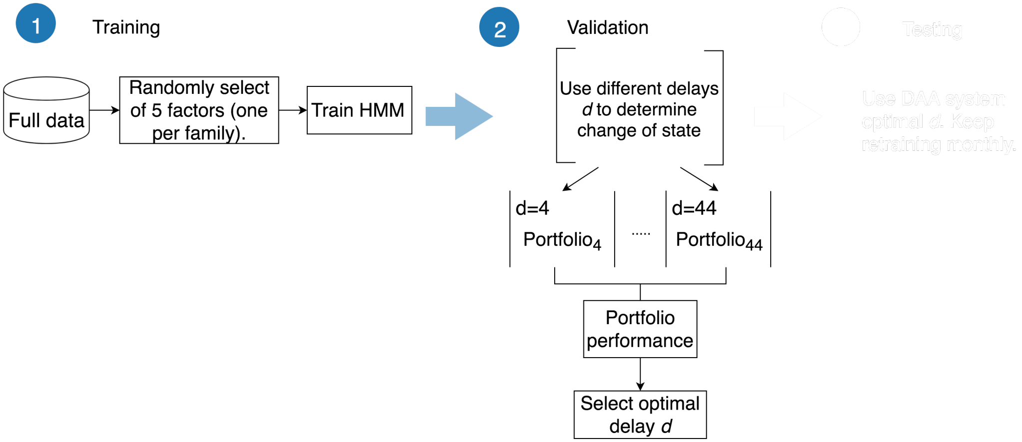

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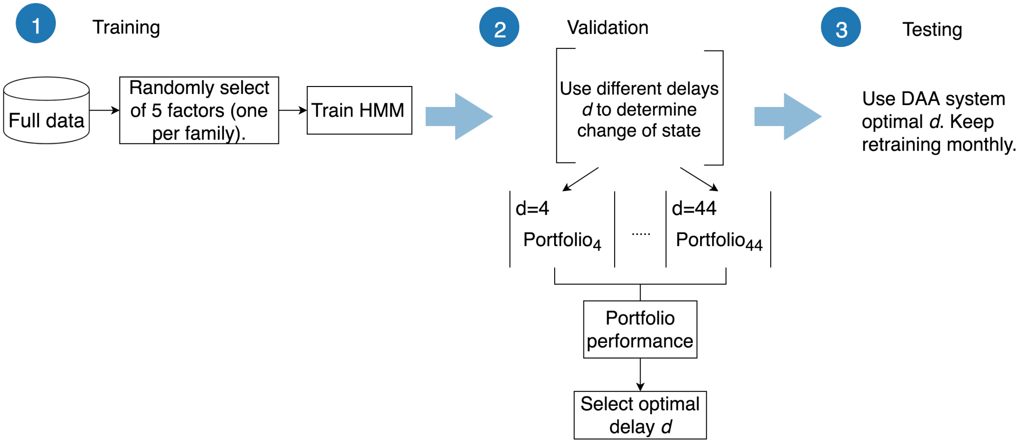

Implementation details

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- Test set is 4 years.
- The model is retrained monthly after the initial training, to account for changes in the parameters (to relax stationarity).

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Three groups of portfolios:

HMM Six portfolios built using information from HMMs.

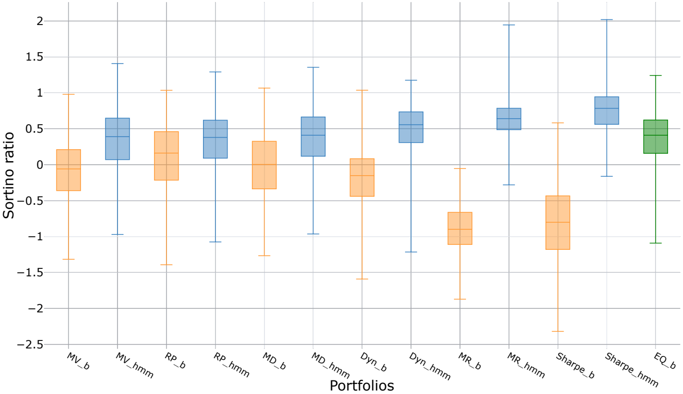
Benchmark 1 Six portfolios rebalanced monthly, single regime.

Benchmark 2 Equally weighted portfolio rebalanced monthly.

Total $= (6 + 6 + 1) * 1260$ portfolios.

Main results part 1

- Blue: HMM portfolios
- Orange: no-regime portfolios
- Green: EQ portfolio.



Main results part 1

	Ann ret	Ann vol	IR	Skw	kurt	D. risk	Sortino	DD	DD days
EQ	0.77	2.88	0.26	-0.14	0.81	2.05	0.37	379	318
Dyn HMM	1.67	4.73	0.34	-0.19	1.35	3.37	0.48	32	291
Dyn Bench	-0.60	3.98	-0.14	-0.40	1.68	2.96	-0.19	1136	682
Sharpe HMM	2.31	4.66	0.53	-0.19	1.16	3.29	0.75	429	253
Sharpe Bench	-3.14	4.89	-0.64	-0.79	4.49	3.80	-0.82	1375	873
MR HMM	3.19	7.03	0.46	-0.19	1.34	4.98	0.65	35	264
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MV HMM	0.61	2.41	0.24	-0.14	0.96	1.72	0.35	662	309
MV Bench	-0.12	2.24	-0.07	-0.11	0.83	1.61	-0.09	520	511
MD HMM	0.69	2.54	0.26	-0.14	1.01	1.80	0.37	340	306
MD Bench	0.01	2.39	-0.02	-0.12	0.84	1.71	-0.02	454	447
RP HMM	0.63	2.58	0.24	-0.13	1.04	1.84	0.34	212	302
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Part 2: Feature selection

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- Traditionally, features to train HMMs are selected in advance (either expert knowledge or data availability). However, these features don't necessarily contribute to regime identification, which is our goal.
- In ML it is customary to use feature selection to improve model performance.
- However unsupervised feature selection research for HMMs is limited.

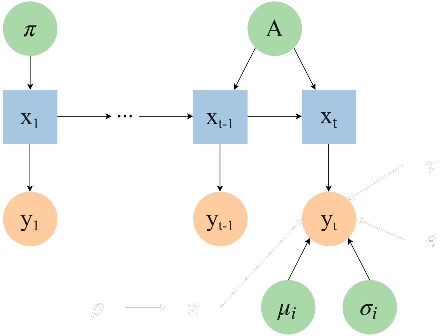
We implemented an embedded feature selection algorithm based on:
Feature Selection for Hidden Markov Models and Hidden Semi-Markov Models Adams et al. (2016)

Feature Saliency HMM

The idea is to divide features into two groups,

- state dependent (good features), modelled by Gaussians that are state dependent with parameters μ_i and σ_i
- state independent (irrelevant features), modelled by gaussians with parameters τ and ϵ.

ρ (feature saliency) is the probability that the feature is relevant.



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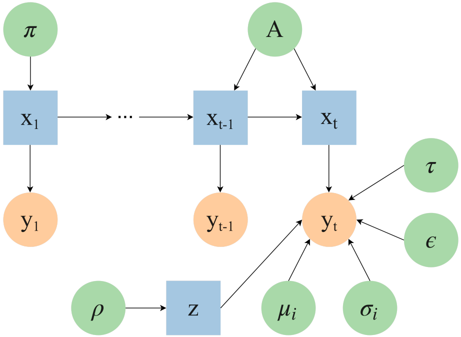
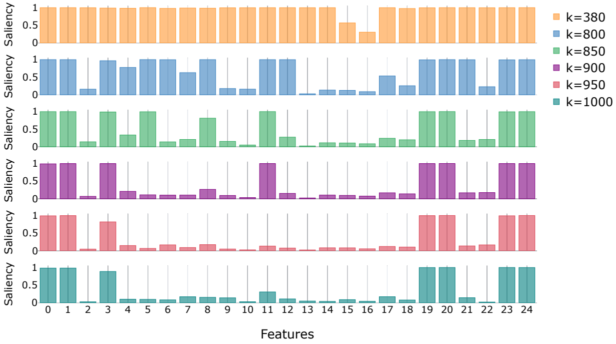


Relevant Features

- k is a hyper-parameter that can be used as cost of the feature. The higher its value, the less features will be selected.



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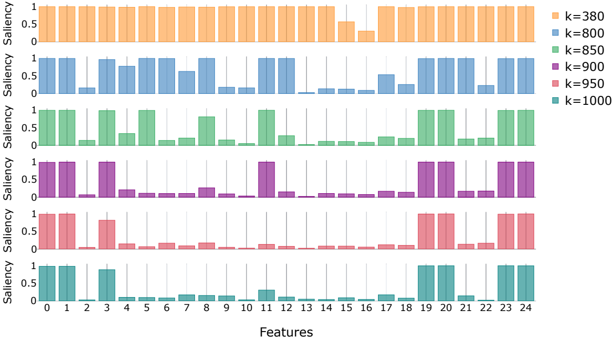

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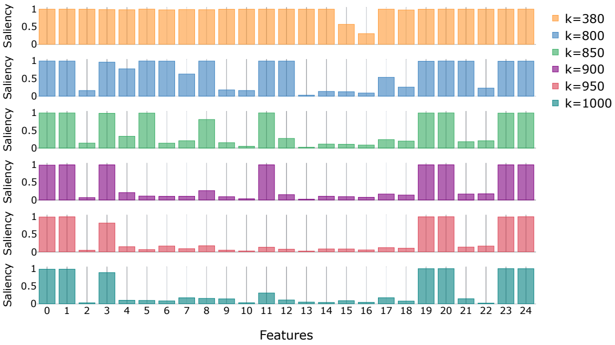
- We can see that the selected parameters are stable, and after a value of k above 850, the number of features doesn't change much.
- Selected factors are: Book Value Yield, 1 Yr Fwd Earnings Yield, Sales Yield, 6 Month Price Momentum, 12 Month Price Momentum, EPSCV, Beta.



DAA system with FSHMM

To test the DAA system incorporating the FS algorithm, we built two cases:

- Trained one HMM with all 25 features.
- Trained one HMM with the relevant subset of features.

FSHMM tends to be more sensible to the distress state - it spends 24% of the time in this state versus 20% of the model trained with full set of features.

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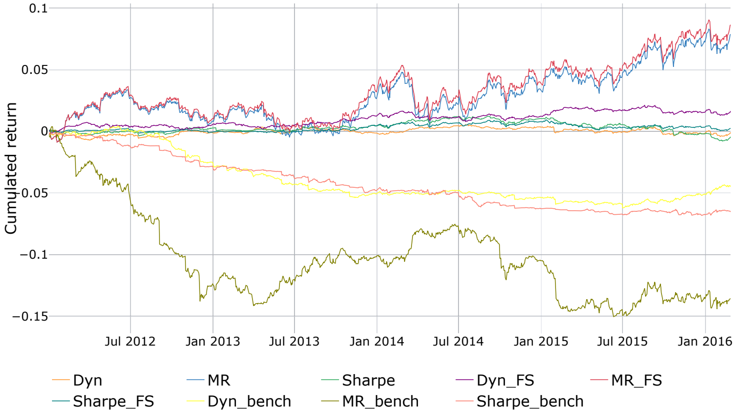
Same DAA system as before, with daily evaluation of the state and monthly retraining.

- For the allocation, we used MSCI factor indices, so we had to estimate the mean and covariance for each regime.
- We built Dynamic, Max return and Sharpe portfolios only.

Main results part 2



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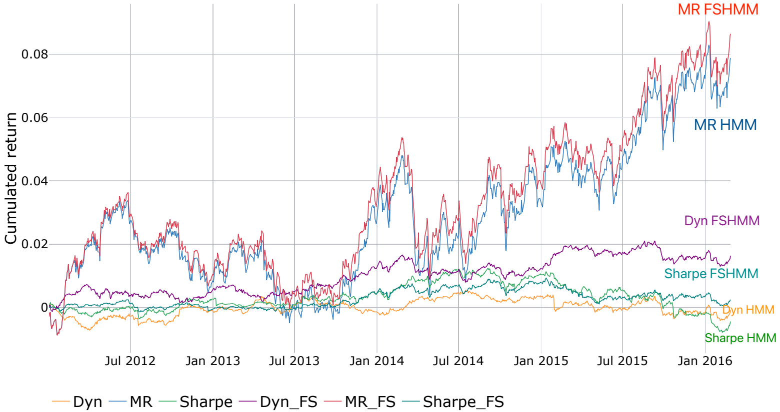

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Sharpe HMM	-0.11	0.65	-0.16	-0.70	3.84	0.49	-0.22	-164	522
Sharpe Bench	-1.62	0.92	-1.76	-2.75	15.0	0.82	-1.98	19825	1452
Dyn FSHMM	0.39	0.65	0.61	-0.41	0.84	0.47	0.84	-52	141
Dyn HMM	-0.02	0.60	-0.03	-1.12	9.03	0.45	-0.04	-175	566
Dyn Bench	-1.10	1.03	-1.07	-2.76	16.2	0.88	-1.24	-1508	1123
MR FSHMM	2.02	3.20	0.63	-0.39	1.83	2.30	0.88	-82	62
MR HMM	1.85	3.19	0.58	-0.39	1.84	2.29	0.80	-92	62
MR Bench	-3.46	3.78	-0.91	-2.71	20.5	3.17	-1.09	-4032	1250
MSCI Quality	0.50	2.76	0.18	0.20	2.02	1.90	0.26	-208	837
MSCI Enhanced Value	0.03	3.97	0.01	0.029	0.86	2.83	0.01	-105	599
MSCI High Dividend Yield	-2.16	3.22	-0.67	0.38	0.85	2.24	-0.96	-2374	1317
MSCI Momentum	2.48	4.35	0.57	-0.35	1.42	3.11	0.80	-144	475
MSCI Minimum Volatility	-0.89	3.58	-0.25	0.10	0.69	2.52	-0.35	-38371	906
MSCI Equal Weighted	-0.27	2.94	-0.09	-0.045	0.74	2.09	-0.13	-135	675

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4. We tested both models using MSCI USA enhanced factor indices. Portfolios constructed using feature saliency HMM show a higher performance than the same portfolios constructed using full-feature HMM.

Future Work

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3. A drawback of using HMMs is selecting the number of latent states beforehand, we could address this using an infinite HMM.

Thank you!

Paper pre-print: https://arxiv.org/abs/1902.10849
or scan QR code!

https://github.com/elifons/FeatureSaliencyHMM