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Experiments on the Application of IOHMMs to Model Financial Returns Series*

Yoshua Bengio[†], Vincent-Philippe Lauzon[‡], and Réjean Ducharme[§]

Résumé / Abstract:

"Input/Output Hidden Markov Models" (IOHMMs) sont des modèles de Markov cachés pour lesquels les probabilités d'émission (et possiblement de transition) peuvent dépendre d'une séquence d'entrée. Par exemple, ces distributions conditionnelles peuvent être linéaires, logistiques, ou non-linéaires (utilisant, par exemple, un réseau de neurones multi-couches). Nous comparons les performances de généralisation de plusieurs modèles qui sont des cas particuliers de IOHMMs pour des problèmes de prédiction de séries financières : une gaussienne inconditionnelle, une gaussienne linéaire conditionnelle, une mixture de gaussiennes, une mixture de gaussiennes linéaires conditionnelles, un modèle de Markov caché, et divers IOHMMs. Les expériences comparent ces modèles sur leurs prédictions de la densité conditionnelle des rendements des indices sectoriels et du marché. Notons qu'une gaussienne inconditionnelle estime le premier moment avec une moyenne historique. Les résultats montrent que, même si la moyenne historique donne les meilleurs résultats pour le premier moment, pour les moments d'ordres supérieurs les IOHMMs performant significativement mieux, comme estimé par la vraisemblance hors-échantillon.

Input/Output Hidden Markov Models (IOHMMs) are conditional hidden Markov models in which the emission (and possibly the transition) probabilities can be conditioned on an input sequence. For example, these conditional distributions can be linear, logistic, or non-linear (using for example multi-layer neural networks). We compare the generalization performance of several models which are special cases of Input/Output Hidden Markov Models on financial time-series prediction tasks: an unconditional Gaussian, a conditional linear Gaussian, a mixture of Gaussians, a mixture of conditional linear Gaussians, a hidden Markov model, and various IOHMMs. The experiments compare these models on predicting the conditional density of returns of market and sector indices. Note that the unconditional Gaussian estimates the first moment with the historical average. The results show that, although for the first moment the historical average gives the best results, for the higher moments, the IOHMMs yielded significantly better performance, as estimated by the out-of-sample likelihood.

Mots clés : Modèles de Markov cachés, IOHMM, séries financières, volatilité

Keywords: *Input/Output Hidden Markov Model (IOHMM), financial series, volatility*

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1 Introduction

Hidden Markov Models (HMMs) are statistical models of sequential data that have been used successfully in many machine learning applications, especially for speech recognition. In recent years, HMMs have been applied to a variety of applications outside of speech recognition, such as handwriting recognition (Nag, Wong and Fallside, 1986; Kundu and Bahl, 1988; Matan et al., 1992; Ha et al., 1993; Schenkel et al., 1993; Schenkel, Guyon and Henderson, 1995; Bengio et al., 1995), pattern recognition in molecular biology (Krogh et al., 1994; Baldi et al., 1995; Chauvin and Baldi, 1995; Karplus et al., 1997; Baldi and Brunak, 1998), and fault-detection (Smyth, 1994). Input-Output Hidden Markov Models (IOHMMs) (Bengio and Frasconi, 1995; Bengio and Frasconi, 1996) (or Conditional HMMs) are HMMs for which the emission and transition distributions are conditional on another sequence, called the input sequence. In that case, the observations modeled with the emission distributions are called outputs, and the model represents the conditional distribution of an output sequence given an input sequence. In this paper we will apply synchronous IOHMMs, for which input and output sequences have the same length. See (Bengio and Bengio, 1996) for a description of asynchronous IOHMMs, and see (Bengio, 1996) for a review of Markovian models in general (including HMMs and IOHMMs), and (Cacciatore and Nowlan, 1994) for a form of recurrent *mixture of experts* similar to IOHMMs.

An IOHMM is a probabilistic model with a chosen fixed number of states corresponding to different conditional distributions of the output variables given the input variables, and with transition probabilities between states that can also depend on the input variables. In the unconditional case, we obtain a Hidden Markov Model (HMM). An IOHMM can be used to predict the conditional density (which includes the expected values as well as higher moments) of the output variables given the current input variables and the past input/output pairs. The most likely state sequence corresponds to a segmentation of the past sequence into regimes (each one associated to one conditional distribution, i.e., to one state), which makes it attractive to model financial or economic data in which different regimes are believed to have existed.

Previous work on using Markov models to represent the non-stationarity in economic and financial time-series due to the business cycle are promising (Hamilton, 1989; Hamilton, 1988) and have generated a lot of interest and generalizations (Diebold, Lee and Weinbach, 1993; Garcia and Perron, 1995; Garcia and Schaller, 1995; Garcia, 1995; Sola and Driffill, 1994; Hamilton, 1996; Krolzig, 1997). In the experiments described here, the conditional dependency is not restricted to an affine form but includes non-linear models such as multi-layer artificial neural networks. Artificial neural networks have already been used in many financial and economic applications (see for example (Moody, 1998) for a survey), including to model some components of the business cycle (Bramson and Hoptroff, 1990; Moody, Levin and Rehfuss, 1993), but not using an IOHMM or conditional Markov-switching model. The main contribution of this paper is in showing a successful application of IOHMMs to a real-world financial data modeling problem, over different types of returns series, revealing some interesting properties of the underlying process by performing comparisons with alternative but related model structures. The IOHMMs and the other models are trained to predict the conditional density of the returns over the next one or more time steps (for daily, weekly,

and monthly data), not only their conditional mean. In this paper, we study and compare for different models the **out-of-sample performance** in terms of predicting the conditional density. Using the out-of-sample performance as a yardstick allows to compare models that have very different numbers of degrees of freedom, and that are not necessarily special cases of each other. The IOHMMs performed better in a statistically significant way in terms of out-of-sample log-likelihood in comparison to a Gaussian model, a HMM, a conditional linear Gaussian model, and a mixture of linear experts (mixture of conditionally linear Gaussian models). However, the Gaussian model outperformed all the others for predicting the mean, and the IOHMMs performed better than models without a state variable, showing that the IOHMM captured non-linear dependencies in the higher moments involving a temporal structure, and that artificial neural networks were useful to capture these non-linearities.

2 Summary of the IOHMM Model and Learning Algorithm

The model of the multivariate discrete time-series data is a mixture of several models, each associated to a sequence of states, or regimes. In each of these regimes, the relation between certain variables of interest may be different and is represented by a different conditional probability model. For each of these regime-specific models, we can use a multi-layer artificial neural network or another conditional distribution model (depending on the nature of the variables). In this paper we experimented with conditionally Gaussian models for each regime, with the dependence being either linear or non-linear (with a neural network). The sequence of states (or regimes) is not observed, but it is assumed to be a Markov chain, with transition probabilities that may depend on the currently observed (or input) variables. In this paper we have only experimented with unconditional transition probabilities. An IOHMM is an extension of Hidden Markov Models (HMMs) to the case of modeling the conditional distribution of an output sequence given an input sequence. Whereas HMMs represent a distribution $P(y_1^T)$ of sequences of (output) observed variables $y_1^T = y_1, y_2, \dots, y_T$, IOHMMs represent a conditional distribution $P(y_1^T | x_1^T)$, given an observed input sequence $x_1^T = x_1, x_2, \dots, x_T$. In the asynchronous case, the lengths of the input and output sequences may be different. See (Bengio, 1996) for a more general discussion of Markovian models which include IOHMMs.

2.1 The Model and its Likelihood

As in HMMs, the representation of the distribution is very much simplified by introducing a discrete state variable q_t (and its sequence q_1^T), and a joint model $P(y_1^T, q_1^T | x_1^T)$, along with two crucial conditional independence assumptions:

$$P(y_t | q_1^t, y_1^{t-1}, x_1^T) = P(y_t | q_t, x_t) \tag{1}$$

$$P(q_{t+1} | q_1^t, y_1^t, x_1^T) = P(q_{t+1} | q_t, x_t) \tag{2}$$

In simple terms, the **state variable** q_t , jointly with the current input x_t , summarize all the relevant past values of the observed and hidden variables when one tries to predict the distribution of the observed variable y_t , or of the next state q_{t+1} .

Because of the above independence assumptions, the joint distribution of the hidden and observed variables can be much simplified, as follows:

$$P(y_1^T, q_1^T | x_1^T) = P(q_1) \prod_{t=1}^{T-1} P(q_{t+1} | q_t, x_t) \prod_{t=1}^T P(y_t | q_t, x_t) \quad (3)$$

The joint distribution is therefore completely specified in terms of (1) the **initial state probabilities** $P(q_1)$, (2) the **transition probabilities** model $P(q_t | q_{t-1}, x_t)$ and, (3) the **emission probabilities** model $P(y_t | q_t, x_t)$. In our experiments we have arbitrarily chosen one of the states (state 0) to be the “initial state”, i.e., $P(q_1 = 0) = 1$ and $P(q_1 > 0) = 0$.

The conditional likelihood of a sequence, $P(y_1^T | x_1^T)$ can be computed recursively, by computing the intermediate quantities $P(y_1^t, q_t | x_1^T)$, for all values of t and q_t , as follows:

$$P(y_1^t, q_t | x_1^T) = P(y_t | q_t, x_t) \sum_{q_{t-1}} P(q_t | q_{t-1}, x_t) P(y_1^{t-1}, q_{t-1} | x_1^T) \quad (4)$$

The recursion is initialized with $P(y_1, q_1 | x_1^T) = P(y_1 | q_1, x_1) P(q_1)$. This recursion is similar to the one used for HMMs, and called the **forward** phase, but for the fact that the probabilities now change with time according to the input values. The computational cost of this recursion is $O(Tm)$ where T is the length of a sequence and m is the number of non-zero transition probabilities at each time step.

Let us note $y_1^{T_p}(p)$ for the p -th sequence of a training data set, of length T_p . The above recursion allows to compute the **log-likelihood** function

$$l(\theta) = \sum_p \log P(y_1^{T_p}(p) | x_1^{T_p}(p), \theta) \quad (5)$$

where θ are parameters of the model which can be tuned in order to maximize the likelihood over the training sequences $\{x_1^{T_p}(p), y_1^{T_p}(p)\}$. Note that we generally drop the conditioning of probabilities on the parameters θ unless the context would make that notation ambiguous.

2.2 Training IOHMMs

For certain types of emission and transition distributions, it is possible to use the EM (Expectation-Maximization) algorithm (Dempster, Laird and Rubin, 1977) to train IOHMMs (see (Bengio and Frasconi, 1996) and (Lauzon, 1999)) to maximize $l(\theta)$ (eq. 5) iteratively. However, in the general case, one has to use a gradient-based numerical optimization algorithm to maximize $l(\theta)$. This is what we have done in the experiments described in this paper, using the conjugate gradient descent algorithm to minimize $-l(\theta)$. The gradient $\frac{\partial l(\theta)}{\partial \theta}$ can be computed analytically by back-propagating through the forward pass computations (eq. 4) and then through the neural network or linear model. The equations for the gradients can be easily obtained, either by hand using the chain rule or using a symbolic computation program such as Mathematica.

2.3 Using a Trained Model

Once the model is trained, it can be used in several ways. If inputs and outputs up to time t (or just inputs up to time t) are given, one can compute the probability of being in each one of the states (i.e, regimes). Using these probabilities, one can make predictions on the output variables (e.g., decision, classification, or prediction) for the current time step, conditional on the current inputs and past inputs/outputs. This prediction is obtained by taking a linear combination of the predictions of the individual regime models,

$$P(y_t|y_1^{t-h}, x_1^t) = \sum_i P(y_t|q_t = i, x_t)P(q_t = i, y_1^{t-h}|x_1^t)$$

where h is called the **horizon** because it is the number of time steps from a prediction to the corresponding observation, i.e., we want to predict y_t given y_{t-h} (and the inputs). The weights of this linear combination are simply the probabilities of being in each one of the states, given the past input/output sequence and the current input:

$$P(q_t = i|x_1^t, y_1^{t-h}) = \frac{P(q_t = i, y_1^{t-h}|x_1^t)}{\sum_i P(q_t = i, y_1^{t-h}|x_1^t)}$$

We can compute recursively

$$P(q_t = i, y_1^{t-h}|x_1^t) = \sum_j P(q_t = i, q_{t-1} = j|x_t)P(q_{t-1} = j, y_1^{t-h}|x_1^{t-1})$$

starting from the $P(q_{t-h} = i, y_1^{t-h}|x_1^{t-h})$ computed in the forward phase (equation 4).

We can also find the most likely sequence of regimes up to the current time step, using the Viterbi algorithm (Viterbi, 1967) (see (Lauzon, 1999) in the context of IOHMMs). The model can also be used as an explanatory tool: given both past and future values of the variables, we can compute the probability of being in each one of the regimes at any given time step t . If a model of the input variables is built, then we can also use the model to make predictions about the future expected state changes. What we will obtain is not just a prediction for the next expected state change, but a distribution over these changes, which also gives a measure of confidence in these predictions. Similarly for the output (prediction or decision) variables, we can train the model to compute the expected value of this variable (given the current state and input), but we can also train it to model the whole distribution (which contains information about the expected error in a particular prediction).

3 Experimental Setup

In this section, we describe the setup of the experiments performed on financial data, for modeling the future returns of Canadian stock market indices. The methodology for estimating and comparing performance is presented: it is based on the out-of-sample behavior of the models when trained sequentially. Using the out-of-sample performance allows to compare very different models, some of which may be much more parsimonious than others, and those

models do not need to be structurally special cases of each other. In subsection 3.1 we describe the mathematical form of each of the compared models. In subsection 3.2, we explain how the out-of-sample measurements are analyzed in order to make a statistical comparison between a pair of models. The central question concerns the estimation of the variance of the difference between the average performance of two models.

Let us first introduce some notation. Let

$$r_t = \text{value}_t / \text{value}_{t-1} - 1$$

be a discrete return series (the ratio of the value of an asset at time t over its value at time $t - 1$, which in the case of stocks includes dividends and capital gains). Let $\bar{r}_{h,t}$ be a moving average of h successive values of r_t :

$$\bar{r}_{h,t} = \frac{1}{h} \sum_{s=t-h+1}^t r_s.$$

In the experiments, we will measure performance in two ways: looking at time t at how well the conditional expectation (first moment) of

$$y_t = \bar{r}_{h,t+h}$$

is modeled, and looking at how well the overall conditional density of y_t is modeled. The distribution is conditioned on the input series x_t . The prediction horizons h in the various experiments were 1, 5, and 12.

In the experiments, all the models \hat{P} are *trained at each time step* t to maximize the conditional likelihood of the training data, $\hat{P}(y_1^{t-h} | x_1^{t-h}, \theta)$, yielding parameters θ_t . We then use the trained model model to infer $\hat{P}(y_t | y_1^{t-h}, x_t, \theta_t)$, and we measure **out-of-sample**

- **SE**, the squared error: $\frac{1}{2}(y_t - \hat{E}[y_t | y_1^{t-h}, x_t, \theta_t])^2$, and
- **NLL**, the negative log-likelihood: $-\log \hat{P}(y_t | y_1^{t-h}, x_t, \theta_t)$,

where $\hat{E}[\cdot | \theta]$ is the expectation under the model distribution $\hat{P}(\cdot | \theta)$. The above logarithm is for making an additive quantity, and the minus is for getting a quantity that should be minimized, like the squared error.

In the experiments we have performed experiments on three types of return series:

1. **Daily market index returns**: we used daily returns data from the TSE300 stock index, from January 1977 to April 1998, for a total of 4154 days. In some experiments daily returns are predicted while in others the daily data series are used to predict returns over 5 days (i.e. one week since there are no measurements for week-ends).
2. **Monthly market index returns**: we used 479 monthly returns from the TSE300 stock index, from February 1956 to January 1996. We also used 24 economic and financial time-series as input variables in some of the models.
3. **Sector returns**: we used monthly returns data for the main 14 sectors of the TSE, from January 1956 to June 1997 inclusively, for a total of at most 497 months (some sectors started later).

3.1 Models Compared

In the experiments, we have compared the following models. All can be considered special cases of IOHMMs, although in some cases an analytic solution to the estimation exists, in other cases the EM algorithm can be applied, while in others only GEM or gradient-based optimization can be performed.

- **Gaussian** model: we have used a diagonal Gaussian model (i.e., not modeling the covariances among the assets). The number of free parameters is $2n$ for n assets. In the experiments $n = 1$ (TSE300) or $n = 14$ (sector indices). There is an analytical solution to the estimation problem. This model is the basic “reference” model to which the other models will be compared.

$$P_g(Y = y|x, \theta) = \prod_{i=1}^n N(y_i; \mu_i, \sigma_i^2)$$

where $N(x; e, v)$ is the Normal probability of observation x with expectation e and variance v , $\theta = (\mu, \sigma)$, and $\mu = (\mu_1, \dots, \mu_n)$, $\sigma = (\sigma_1, \dots, \sigma_n)$. This is like an “unconditional” IOHMM with a single state.

- **Mixture of Gaussians** model: we have used a 2-component mixture in the experiments, whose emissions are diagonal Gaussians:

$$P_m(Y = y|x) = \sum_{j=1}^J w_j P_g(Y = y|x, p_j)$$

where $\theta = (w, p_1, p_2, \dots, p_J)$, p_j is the vector with the means and deviations for the j -th component, and $\sum_j w_j = 1$, $w_j \geq 0$. $J = 2$ in the experiments, to avoid overfitting. The number of free parameters is $J - 1 + 2nJ$. This is like an “unconditional” IOHMM with J states and shared transition probabilities (all the states share the same transition probability distribution to the next states). This means that the model has no “dynamics”: the probability of being in a particular “state” does not depend on what the previous state was.

- **Conditional Linear Gaussian** model: this is basically an ordinary regression, i.e., a Gaussian whose variance is unconditional while its expectation is conditional:

$$P_l(Y = y|x, \theta) = \prod_{i=1}^n N(y_i; b_i + \sum_{k=1}^K A_{i,k} x_k, \sigma_i^2)$$

where $\theta = (A, b, \sigma)$, x_k denotes the k -th element of the input vector. The number of free parameters is $n(2 + K)$. In the experiments, $K = 1, 2, 4, 6, 14$, or 24 inputs have been tried for various input features. See more details below in section 4.

- **Mixture of Conditional Linear Gaussians**: this combines the ideas from the previous two models, i.e., we have a mixture, but the expectations are linearly conditional

on the inputs. We have used separate inputs for each sector prediction:

$$P_{lm}(Y = y|x, \theta) = \sum_{j=1}^J w_j P_l(Y = y|x, p_j)$$

where $\theta = (w, p_1, p_2, \dots, p_J)$, p_j is the parameter vector for a conditional linear Gaussian model, and as usual $w_j \geq 0$, $\sum_j w_j = 1$. The number of free parameters is J times the number of free parameters of the conditional linear Gaussian model, i.e., $nJ(2 + K)$ in the experiments. $J = 2$ in the experiments, and $K = 1, 2, 4, 6, 14, 24$ have been tried. This is like an IOHMM whose transition probabilities are shared across all states. Like for the mixture of Gaussians, this means that the model has no “dynamics”: the probability of being in a particular “state” does not depend on what the previous state was. Note that this model is also called a *mixture of experts* (Jacobs et al., 1991).

- **HMM**: this is like the Gaussian mixture except that the model has dynamics, modeled by the transition probabilities. In the experiments, there are $J = 2$ states. The number of free parameters is $2nJ + J(J - 1)$. This is like an “unconditional” IOHMM. Each emission distribution is an unconditional multinomial: $P(q_t = i | q_{t-1} = j, x_t) = A_{i,j}$. Each emission distribution is a diagonal Gaussian: $P(y_t | q_t = i, x_t) = \prod_{j=1}^n N(y_{t,i}; \mu_{j,i}, \sigma_{j,i}^2)$.
- **Linear IOHMM**: this is like the mixture of experts, but with dynamics (modeled by the transition probabilities), or this is like an HMM in which the Gaussian expectations are affine functions of the input vector. We have not used conditional transition probabilities in the experiments. Again we have used $J = 2$ states, and the number of inputs K varies. The number of free parameters is $nJ(2 + K) + J(J - 1)$.
- **MLP IOHMM**: this is like the linear IOHMM except that the expectations are non-linear functions of the inputs, using a Multi-Layer Perceptron with K inputs and a single hidden layer with H hidden units ($H = 2, 3, \dots$ depending on the experiment). In one set of experiments we have used the same MLP for all the n assets (i.e., a single network per state is used, with n outputs associated to the n assets). In the other experiments, a separate network (with 1 output and K inputs) is used for each asset, so there are n MLPs per state. In the first case the number of free parameters is $J(J - 1) + J(2n + (1 + H)n + H(n + 1))$, and in the second case it is $J(J - 1) + Jn(2 + H + H(K + 1))$.

3.2 Performance Measurements

When comparing the out-of-sample performance of two predictive models on the same data, it is not enough to measure their average performance: we also need to know if the performance difference is significant. In this section we explain how we have answered this question, using an estimator of the variance of the difference in average out-of-sample performance of time-series models.

In the experiments on sectors, there are several assets, with corresponding return series. Different models are trained separately on each of the assets, and the results reported below concern the average performance over all the assets. We have measured the average squared

error (MSE) and the average negative log-likelihood (NLL). We have also estimated the variance of these averages, and the variance of the difference between the performance for one model and the performance for another model, as described below. Using the latter, we have tested the null hypothesis that two compared models have identical true generalization. For this purpose, we have used an estimate of variance that takes into account the dependencies among the errors at successive time steps. Let e_t be a series of errors (or error differences), which are maybe not *i.i.d.* Their average is

$$\bar{e} = \frac{1}{n} \sum_{t=1}^n e_t,$$

assumed approximately Normal. We are interested in estimating the variance

$$Var[\bar{e}] = \frac{1}{n^2} \sum_{t=1}^n \sum_{t'=1}^n Cov(e_t, e_{t'}).$$

Note that e_t 's form a series of out-of-sample performances, and unlike a series of in-sample residues it may have autocorrelations, even if the model has been properly trained. A plot of the auto-correlation function of e_t (both for the NLL sequence and the difference in NLL for two models) show the presence of significant auto-correlations. Since we are dealing with a time-series, and because we do not know how to estimate independently and reliably all the above covariances, we assumed that the error series is covariance-stationary and that the covariance dies out as $|t - t'|$ increases.

Because there are generally strong dependencies between the errors of different models, we have found that much better estimates of variance were obtained by analyzing the differences of squared errors, rather than computing a variance separately for each average:

$$Var[\bar{e}_i^A - \bar{e}_i^B] = Var[\bar{e}_i^A] + Var[\bar{e}_i^B] - 2Cov[\bar{e}_i^A, \bar{e}_i^B]$$

where \bar{e}_i^A is the average error of model A on asset i , and similarly for B . Note that to take the covariance into account, it is not sufficient to look at the average out-of-sample performance for each model.

The average over assets of the performance measure is simply the average of the average errors for each asset:

$$\bar{e}^A = \frac{1}{n} \sum_{i=1}^n \bar{e}_i^A.$$

To combine the variances obtained as above for each of the assets, we decompose the variance of the average over assets as follows:

$$Var\left[\frac{1}{n} \sum_{i=1}^n (\bar{e}_i^A - \bar{e}_i^B)\right] = \frac{1}{n^2} \sum_{i=1}^n Var[\bar{e}_i^A - \bar{e}_i^B] + \frac{2}{n^2} \sum_{i=1}^n \sum_{j < i} Cov[\bar{e}_i^A - \bar{e}_i^B, \bar{e}_j^A - \bar{e}_j^B]$$

where the covariances are estimated by the sample covariances of the averages of the error differences:

$$Cov[\bar{e}_i^A - \bar{e}_i^B, \bar{e}_j^A - \bar{e}_j^B] \approx \frac{1}{T(T-1)} \sum_{t=1}^T (e_{t,i}^A - \bar{e}_i^A - e_{t,i}^B + \bar{e}_i^B)(e_{t,j}^A - \bar{e}_j^A - e_{t,j}^B + \bar{e}_j^B)$$

In the tables below, we give the p-value of the null hypothesis that model A is not better than model B (where model A is a reference model, such as the best-performing model). In the case that $\bar{e}^A < \bar{e}^B$, the alternative hypothesis is that A is better than B (so we use a single-sided test, with p-value = $P(E[e^B] - E[e^A] \geq \bar{e}^B - \bar{e}^A)$). In the opposite case, we consider the converse test (with the alternative hypothesis being that B is better than A).

4 Experimental Results

Each of the tables in this section gives the result of a series of experiments in which the output variable is the same, and we vary the choice of model and input variables (when the model is conditional).

To explain some of the details of the input variables used in the experiments, let us define the following measure of return variation:

$$v_t = |r_t - \bar{r}_{t,t}|$$

where $\bar{r}_{t,t}$ is the historical average of the returns up to time t , and $\bar{v}_{d,t}$ is a d -time steps moving average of v_t available at time t .

The following target output variables have been considered:

- **TSE300 5-day** return: we want to predict the conditional density of the 5-day average future market index return $y_t = \bar{r}_{5,t+5}$ at time t (t on a daily scale); horizon $h = 5$.
- **TSE300 12-month** return: we want to predict the conditional density of the 1-year average future market index return $y_t = \bar{r}_{12,t+12}$ at time t (t on a monthly scale); horizon $h = 12$.
- **TSE300 1-month** return: we want to predict the conditional density of next month's market index return $y_t = r_{t+1}$ at time t (t on a monthly scale); horizon $h = 1$.
- **14 sectors 1-month** return: we want to predict the individual conditional density of next month's return for each of the 14 sector indices of the Toronto Stock Exchange, $y_t = r_{t+1}$, at time t (t on a monthly scale); horizon $h = 1$.

The following input variables have been considered in the experiments (when the number of inputs used is n , it is shown in the tables with $K = n$ besides the model structure):

- **1 input**: the current return r_t associated to the output series.
- **2 inputs**: the current return r_t and current variation v_t .
- **4 inputs**: the current return r_t , current variation v_t , and the average past 4 returns and variations $\bar{r}_{4,t}$ and $\bar{v}_{4,t}$.
- **12 inputs**: the current return r_t , current variation v_t , the average past 4 returns and variations $\bar{r}_{4,t}$ and $\bar{v}_{4,t}$, and the average past 12 returns and variations $\bar{r}_{12,t}$ and $\bar{v}_{12,t}$.

- **14 inputs:** the 14 current sector returns.
- **24 inputs:** 24 economic and financial indicators of the Canadian financial markets: the first input is the historical average of the TSE300 market index, the next two variables are two Canadian interest rates, the next 6 variables are estimated risk premia for various assets, the next 2 variables are two measures of return-on-equity for the Canadian market, and the last 13 provide the shape of the interest rate curve.

In the tables, the column entitled “ $\widehat{MSE}(sdev)$ ” gives the average squared error and the estimated standard deviation of that average (in parenthesis). A similar column is provided for the negative log-likelihood (NLL). The performance figure in bold is the lowest (i.e. the best) in the column. The column entitled “p-value (%) vs Gaussian” gives the p-value (in percent) of a single-sided test for the null hypothesis that the model is not better in NLL than the Gaussian reference. If there is no “W” before the percentage, the alternative hypothesis is that the model is better than the reference; if there is a “W” then the test is with respect to the alternative hypothesis that the reference is better than the model. Similarly, the column entitled “p-value (%) vs M” compares each of the model with model M (which is the one with the lowest NLL). For this column there never is a “W” since the comparison is always against the “best” model, so we are testing with respect to the alternative hypothesis that the given model is worse than the “best” model. For both p-value columns, bold figures underline the fact that the p-value is less than 5%, i.e., that we consider that the null hypothesis of no difference should be rejected. Since in all comparisons no model significantly improved on the Gaussian for predicting the first moment (i.e., with respect to mean squared error), we have only given the p-values for comparing the negative log-likelihoods. *Note that the p-values take into account not only the variances of each model’s performance but also their covariance, which is generally positive (hence the variance of their difference is much smaller than the sum of their variance).*

| | $\widehat{MSE}(sdev)$ $\times 10^{-6}$ | $\widehat{NLL}(sdev)$ | p-value (%) vs Gaussian | p-value(%) vs IOHMM (MLP) |
|-------------------------|---|-----------------------|----------------------------|------------------------------|
| Gaussian | 6.73 (1.29) | -4.171 (0.064) | | < 1e-7 |
| Gaussian Mixture | 6.73 (1.29) | -4.241 (0.044) | 0.41 | < 1e-7 |
| HMM | 6.74 (1.30) | -4.257 (0.046) | 0.02 | < 1e-7 |
| Linear (K=4) | 6.87 (1.41) | -4.180 (0.062) | 1.47 | < 1e-7 |
| Mixture of Linear (K=4) | 6.79 (1.34) | -4.261 (0.041) | 0.25 | 1.31e-3 |
| IOHMM (Linear K=4) | 6.94 (1.39) | -4.277 (0.059) | < 1e-7 | 5.80e-3 |
| IOHMM (MLP H=2,K=4) | 6.96 (1.35) | -4.332 (0.052) | < 1e-7 | |

Table 1: Results on modeling the next **TSE300 5-day** returns every day. Bold MSE or NLL shows the best value obtained. Bold p-values are < 5%, suggesting that the difference with the reference is significant.

In table 1 and figure 1 the results on predicting the 5-day return of the TSE300 are presented. All the conditional models use the 4 inputs variables. No model outperforms

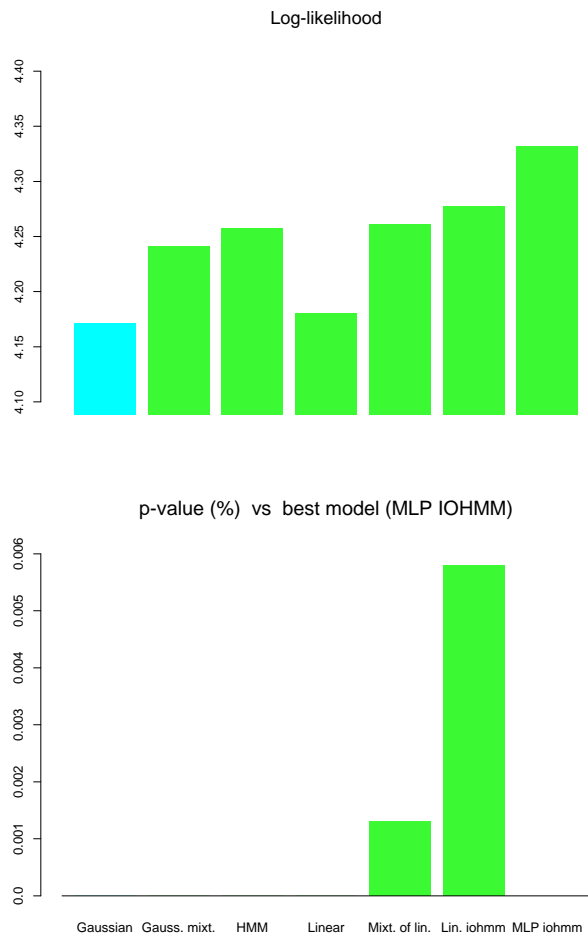


Figure 1: Comparative results on modeling the conditional density of the next **TSE300 5-day** returns every day. Top: out-of-sample log-likelihood. Bottom: p-value vs MLP IOHMM.

the Gaussian for predicting the first moment, but all of them outperform the Gaussian for predicting the conditional density. As in all of the other experiments, the Gaussian model gives the lowest MSE (error in prediction of the first moment), but the difference with the other models is not significant. For predicting the conditional density, the best model is the non-linear IOHMM (with a MLP), and the difference with each of the other models is significant. The following differences are also significant: the HMM is significantly better than the Gaussian mixture (p-value = 1.1%, showing that state information is important), the conditionally linear mixture is significantly better than the unconditional mixture (p-value = 0.16%, showing that the inputs are useful to predict the distribution of the future returns) and the linear IOHMM is significantly better than the mixture of conditionally linear mixture (p-value = 2.54%, showing that even with conditioning inputs, the hidden state variable remains useful). In addition, the table shows that the non-linearity in the IOHMM is important to get further improvement (it is not always the case with the other data sets). In figure 2 are shown examples of the shape of the predicted conditional densities for three of the models, out-of-sample, on this data series. Note the flatter shape of the density for the two IOHMMs (around 1 to 2% change in price).

| | $\widehat{MSE}(sdev)$ $\times 10^{-5}$ | $\widehat{NLL}(sdev)$ | p-value (%) Gaussian | p-value(%) vs IOHMM (MLP) |
|-------------------------|---|-----------------------|-------------------------|------------------------------|
| Gaussian | 9.69 (2.13) | -2.89 (0.12) | | < 1e-7 |
| Mixture Gaussian | 9.69 (2.13) | -2.89 (0.12) | 28.14 | < 1e-7 |
| HMM | 10.00 (2.17) | -2.97 (0.12) | 0.0043 | 5.40e-3 |
| Cond. Linear (K=1) | 10.13 (2.54) | -2.90 (0.14) | 38.71 | 2.51e-3 |
| Mixture of Linear (K=1) | 10.04 (2.49) | -2.91 (0.13) | 27.93 | 4.17e-4 |
| IOHMM (Linear K=1) | 10.15 (2.54) | -2.94 (0.14) | 10.53 | 2.95e-4 |
| IOHMM (MLP H=2, K=1) | 10.42 (2.35) | -3.17 (0.12) | < 1e-7 | |

Table 2: Results on modeling the next **TSE300 12-month** returns every month. Bold MSE or NLL shows the best value obtained. Bold p-values are < 5%, suggesting that the difference with the reference is significant.

In table 2 and figure 3, the results of experiments on the monthly TSE300 data are presented, with a horizon of $h = 12$ months, i.e., the models predict every month the conditional density of the next 12-month TSE300 market index return. Note that only the non-linear IOHMM and the HMM give a significantly better model than the Gaussian, and note that the non-linear IOHMM is significantly better than all the others.

In table 3 and figure 4, the results of experiments on the monthly TSE300 data are presented. Almost all the models (except two of the linear models) are significantly better than the Gaussian for modeling the density of the next month return. The best model is the linear IOHMM, and its performance is significantly better than the performance of the other models. Note also that the models with the 24 inputs (which include not only technical but also economic variables) outperform the models with only technical variables in input.

Table 4 and figure 5 shows the results of experiments on jointly modeling the conditional

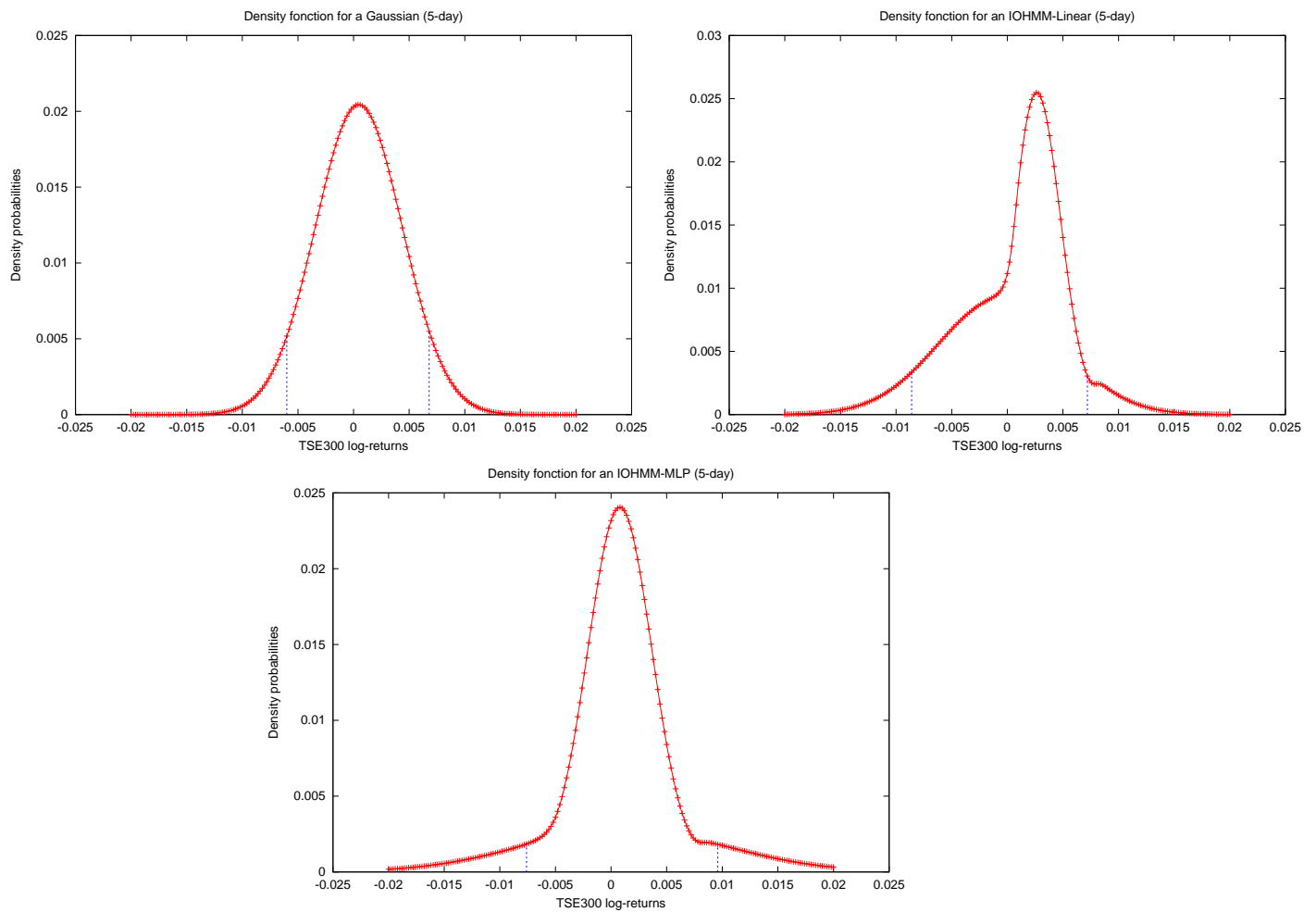


Figure 2: Comparison of the shape of the conditional densities predicted for the same time step (out-of-sample) for three models of the 5-day TSE300 log-returns: Gaussian (left), linear IOHMM (middle), non-linear IOHMM (right). The vertical bars show a 90% confidence interval around the expected return.

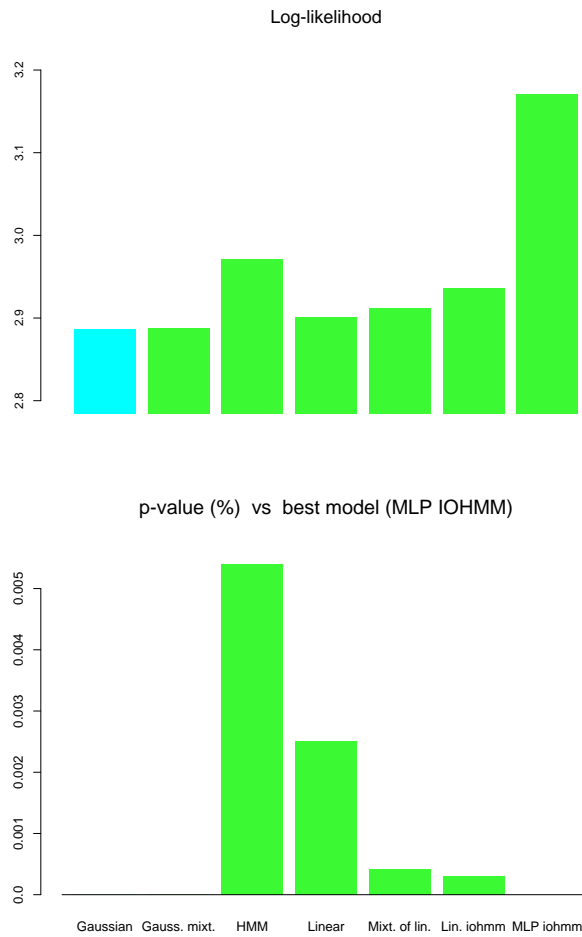


Figure 3: Comparative results on modeling the conditional density of the next **TSE300 12-month** returns every month. Top: out-of-sample log-likelihood. Bottom: p-value vs MLP IOHMM.

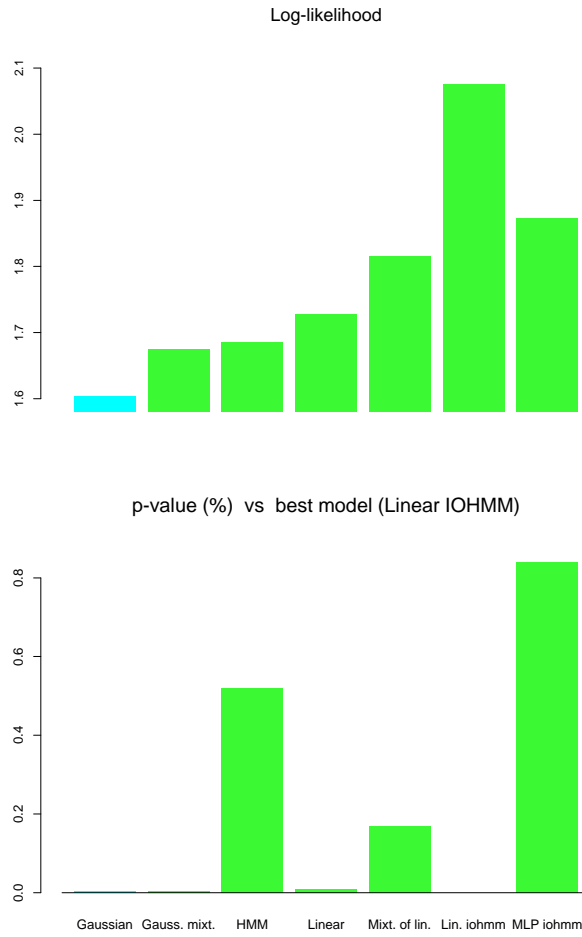


Figure 4: Comparative results on modeling the conditional density of the next **TSE300 1-month** returns every month. Top: out-of-sample log-likelihood. Bottom: p-value vs Linear IOHMM ($K = 24$).

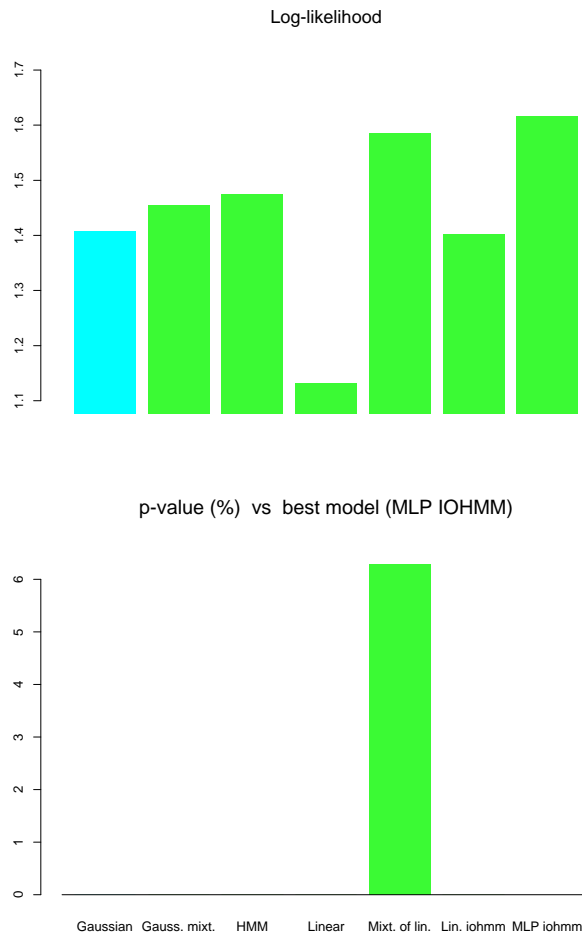


Figure 5: Comparative results on jointly modeling the conditional density of the next **TSE 14 sectors 1-month** returns every month. Top: out-of-sample log-likelihood. Bottom: p-value vs MLP IOHMM ($K = 24$).

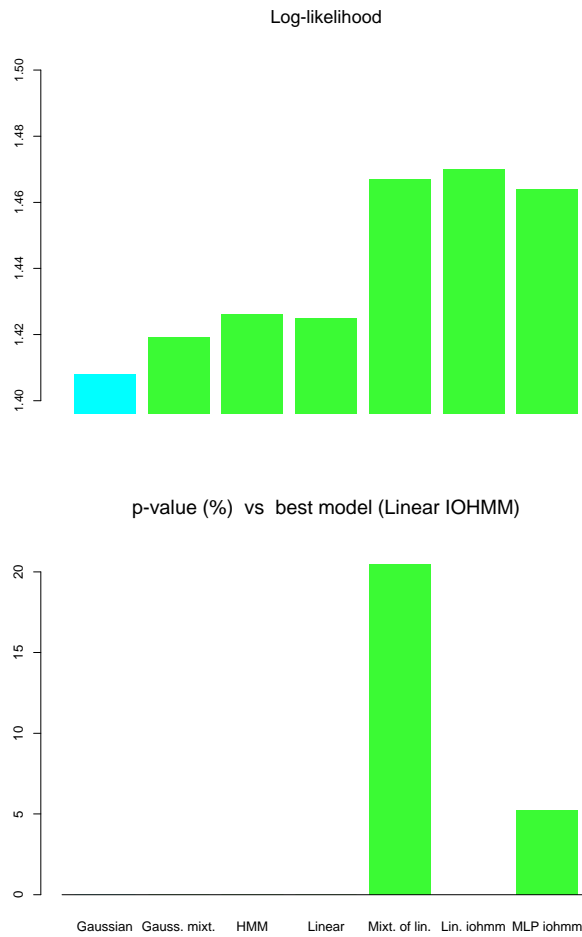


Figure 6: Comparative results on separately modeling the conditional density of the next **TSE 14 sectors 1-month** returns every month. Top: out-of-sample log-likelihood. Bottom: p-value vs Linear IOHMM ($K = 6$).

| | $\widehat{MSE}(sdev)$ $\times 10^{-3}$ | $\widehat{NLL}(sdev)$ | p-value (%) vs Gaussian | p-value(%) vs IOHMM (K=24) |
|--------------------------|---|-----------------------|----------------------------|----------------------------------|
| Gaussian | 1.22 (0.20) | -1.60 (0.08) | | 3.49e-3 |
| Mixture Gaussian | 1.22 (0.20) | -1.68 (0.07) | 0.28 | 0.046 |
| HMM | 1.23 (0.21) | -1.69 (0.07) | 0.059 | 0.52 |
| Cond. Linear (K=4) | 1.25 (0.20) | -1.63 (0.07) | 6.51 | 0.086 |
| Cond. Linear (K=6) | 1.28 (0.21) | -1.63 (0.07) | 7.62 | 0.084 |
| Cond. Linear (K=24) | 2.12 (0.45) | -1.73 (0.07) | 0.18 | 7.69e-3 |
| Mixture of Linear (K=4) | 1.25 (0.20) | -1.74 (0.06) | 0.025 | 0.72 |
| Mixture of Linear (K=6) | 1.32 (0.22) | -1.74 (0.06) | 0.096 | 0.45 |
| Mixture of Linear (K=24) | 2.97 (0.70) | -1.81 (0.09) | 0.57 | 0.17 |
| IOHMM (Linear K=4) | 1.31 (0.22) | -1.73 (0.06) | 0.013 | 0.74 |
| IOHMM (Linear K=6) | 1.39 (0.24) | -1.74 (0.05) | 0.13 | 0.32 |
| IOHMM (Linear K=24) | 2.27 (0.48) | -2.08 (0.09) | 3.49e-3 | |
| IOHMM (MLP H=3, K=4) | 1.25 (0.20) | -1.75 (0.06) | 4.86e-3 | 0.090 |
| IOHMM (MLP H=3, K=6) | 1.36 (0.22) | -1.76 (0.06) | 2.56e-3 | 0.25 |
| IOHMM (MLP H=2, K=24) | 1.42 (0.21) | -1.87 (0.06) | < 1e-7 | 0.84 |

Table 3: Results on modeling the next **TSE300 1-month** returns. Bold MSE or NLL shows the best value obtained. Bold p-values are $< 5\%$, suggesting that the difference with the reference is significant.

density of the next month’s return for the 14 sector indices. All the conditional models have 14 inputs, for the current return of each of the 14 sectors. The non-linear IOHMM yields the best results, significantly above all the other models except the mixture of linear experts (but the p-value is close to our threshold, at 6.3%). We have also tried to model the **relative returns** of the sectors with respect to the market index, and the results are shown in table 5. Again, the non-linear IOHMM performed best in NLL, but here the difference with the linear IOHMM is not statistically significant.

In table 6 and figure 6, the results of the other experiments on the monthly 14 sectors of the TSE300 data are presented, where each sector has been trained individually. For predicting the conditional density, the Gaussian is beaten significantly by all the other models. The best-performing model is one of the linear IOHMMs. It outperforms significantly all the models except an IOHMM with MLP (5 hidden units, 1 input) and the mixture of linear experts (with 6 inputs).

5 Conclusions

In this paper we have applied Input/Output Hidden Markov Models to financial time-series data in a number of comparative experiments aimed at measuring the expected generalization

| | $\widehat{MSE}(sdev)$ $\times 10^{-3}$ | $\widehat{NLL}(sdev)$ | p-value (%) vs Gaussian | p-value(%) vs IOHMM (MLP) |
|--------------------------|---|-----------------------|----------------------------|---------------------------------|
| Gaussian | 2.02 (0.19) | -1.41 (0.05) | | < 1e-7 |
| Mixture Gaussian | 2.02 (0.19) | -1.46 (0.05) | < 1e-7 | < 1e-7 |
| HMM | 2.02 (0.19) | -1.47 (0.04) | 9.53e-5 | < 1e-7 |
| Cond. Linear (K=14) | 2.49 (0.20) | -1.13 (0.14) | W4.32e-4 | < 1e-7 |
| Mixture of Linear (K=14) | 2.18 (0.19) | -1.59 (0.04) | 2.98e-6 | 6.29 |
| IOHMM (Linear K=14) | 2.29 (0.22) | -1.40 (0.10) | W47.56 | < 1e-7 |
| IOHMM (MLP H=2, K=14) | 2.09 (0.18) | -1.62 (0.04) | < 1e-7 | |

Table 4: Results on jointly modeling the next **14 sectors 1-month** returns (one model used for all the sectors). Bold MSE or NLL shows the best value obtained. Bold p-values are < 5%, suggesting that the difference with the reference is significant.

error of different types of model structures. The main conclusions from the experiments are the following:

- For predicting the expected future returns, none of the models we have tried performs better than the simple-minded historical average, i.e., *we get better predictions of the mean using an unconditional model.*
- For predicting the future distribution of the returns at a fixed horizon, we have found IOHMMs to perform significantly better than other models, more specifically:
 - For predicting the next 5-day return of the TSE300, the non-linear IOHMM (with MLPs) is significantly better than all the other models.
 - For predicting the next 12-month return of the TSE300, the non-linear IOHMM (with MLPs) is significantly better than all the other tested models.
 - For predicting the next 1-month return of the TSE300, the linear IOHMM with fundamental economic input variables is significantly better than all the other models.
 - For predicting the next 1-month return of the 14 sector indices,
 - * when predicting all 14 sectors simultaneously, the non-linear IOHMM (with MLPs) is significantly better than all the other tested models (except the mixture of linear experts, against which the p-value is 6.3%).
 - * when predicting all 14 sectors simultaneously, one of the linear IOHMMs is significantly better than most other models except a non-linear IOHMM and a mixture of linear experts.

By looking over these results and trying to answer qualitative questions about which type of models make better predictions, we find that the results broadly suggest that *for predicting*

| | $\widehat{MSE}(sdev)$ $\times 10^{-3}$ | $\widehat{NLL}(sdev)$ | p-value (%) vs Gaussian | p-value(%) vs IOHMM (MLP) |
|--------------------------|---|-----------------------|----------------------------|---------------------------------|
| Gaussian | 0.994 (0.071) | -1.81 (0.036) | | 3.0e-6 |
| Mixture Gaussian | 0.994 (0.071) | -1.81 (0.036) | 1.46e-4 | 3.0e-6 |
| HMM | 0.994 (0.071) | -1.81 (0.036) | 9.96e-1 | 3.0e-6 |
| Cond. Linear (K=14) | 1.14 (0.083) | -1.82 (0.035) | 41.13 | < 1e-7 |
| Mixture of Linear (K=14) | 1.14 (0.083) | -1.87 (0.025) | 9.73e-3 | 1.32 |
| IOHMM (Linear K=14) | 1.23 (0.088) | -1.89 (0.026) | 7.44e-1 | 47.29 |
| IOHMM (MLP H=2, K=14) | 1.05 (0.077) | -1.89 (0.029) | 2.98e-6 | |

Table 5: Results on jointly modeling the next **14 sectors 1-month** relative returns (with respect to the TSE300 index). Bold MSE or NLL shows the best value obtained. Bold p-values are < 5%, suggesting that the difference with the reference is significant.

the density of the next returns or relative returns, (1) conditional models perform better, (2) using a state variable that can deal with regime changes yields better performance, (3) combining both conditional predictions and a state variable yields even better results, and in most cases (4) non-linear predictions associated to each state yield even better results than linear predictions.

There are many more experiments and analyses that should be done in order to pursue in the direction explored here. Most interestingly, we would like to ascertain whether the improvements in likelihood brought by the various mixture models, and in particular the IOHMMs, can be used in order to improve financial decision-taking, e.g., for assessing risk in portfolio management or for trading options. Also, in view of the fact that the model is good at predicting higher moments, it would be interesting to apply it as a risk-assessing tool (for example to evaluate value-at-risk) rather than as a tool to predict expected returns. It might be used as such (for controlling risk), or incorporated in a system that trades on predictions of volatility. Another type of application of the IOHMM is as a generative model for parametric bootstrap. The IOHMM could thus be used to generate many alternative plausible histories, over which the variability of any learning algorithm (for example the variability of its out-of-sample performance) could be assessed.

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| | $\widehat{MSE}(sdev)$ $\times 10^{-3}$ | $\widehat{NLL}(sdev)$ | p-value (%) vs Gaussian | p-value(%) vs Lin. IOHMM (K=6) |
|-------------------------|---|-----------------------|----------------------------|--------------------------------------|
| Gaussian | 2.017 (.080) | -1.408 (.019) | | < 1e-7 |
| Mixture Gaussian | 2.017 (.080) | -1.419 (.018) | 2.53e-4 | < 1e-7 |
| HMM | 2.017 (.080) | -1.426 (.018) | 7.74e-5 | < 1e-7 |
| Cond. Linear (K=1) | 2.013 (.081) | -1.417 (.018) | 0.31 | < 1e-7 |
| Cond. Linear (K=2) | 2.030 (.081) | -1.421 (.018) | 0.17 | < 1e-7 |
| Cond. Linear (K=4) | 2.049 (.082) | -1.425 (.018) | 0.073 | < 1e-7 |
| Cond. Linear (K=6) | 2.064 (.083) | -1.423 (.018) | 0.097 | < 1e-7 |
| Mixture of Linear (K=1) | 2.014 (.080) | -1.430 (.018) | 5.96e-6 | < 1e-7 |
| Mixture of Linear (K=2) | 2.030 (.081) | -1.436 (.018) | 5.96e-6 | < 1e-7 |
| Mixture of Linear (K=4) | 2.048 (.081) | -1.458 (.016) | < 1e-7 | 0.024 |
| Mixture of Linear (K=6) | 2.061 (.082) | -1.467 (.016) | < 1e-7 | 20.48 |
| IOHMM (Linear K=1) | 2.015 (.081) | -1.431 (.018) | < 1e-7 | < 1e-7 |
| IOHMM (Linear K=2) | 2.031 (.081) | -1.439 (.018) | 5.96e-6 | < 1e-7 |
| IOHMM (Linear K=4) | 2.050 (.081) | -1.461 (.016) | < 1e-7 | 1.06 |
| IOHMM (Linear K=6) | 2.073 (.083) | -1.470 (.016) | < 1e-7 | |
| IOHMM (MLP H=5, K=1) | 2.022 (.080) | -1.464 (.017) | < 1e-7 | 5.26 |
| IOHMM (MLP H=5, K=2) | 2.051 (.081) | -1.446 (.016) | < 1e-7 | 8.94e-6 |
| IOHMM (MLP H=3, K=4) | 2.032 (.079) | -1.445 (.017) | < 1e-7 | 2.68e-5 |
| IOHMM (MLP H=2, K=6) | 2.035 (.081) | -1.443 (.017) | < 1e-7 | < 1e-7 |

Table 6: Results on modeling the **TSE300 14 sectors (1-month)** returns, with a separate model for each sector. Bold MSE or NLL shows the best value obtained. Bold p-values are < 5%, suggesting that the difference with the reference is significant.

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