Covariate-dependence copula model based on web semantics

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Idea

- Measuring the dependence of financial market
- News will have an impact on financial market volatility

Sklar's theorem

In a bi-variate setting: let F_{xy} be a joint distribution with margins F_x and F_y . Then exist a function C, such that:

sklar's theorem

$$F_{xy}(x,y) = F(F_1^{-1}(u_1), F_2^{-1}(u_2)) = C(F_x(x), F_y(y))$$

If X and Y are continuous, then C is unique. Conversely if C is a copula function and F_x and F_y are distribution functions, then the function F_{xy} is a joint distribution with margins F_x and F_y .

Tail-dependence

$$\lambda_L = \lim_{u \to 0^+} p(X_1 < F_1^{-1}(u)|X_2 < F_2^{-1}(u)) = \lim_{u \to 0^+} \frac{C(u, u)}{u}$$

$$\lambda_U = \lim_{u \to 1^-} p(X_1 > F_1^{-1}(u)|X_2 > F_2^{-1}(u)) = \lim_{u \to 1^-} \frac{1 - 2u + C(u, u)}{1 - u}$$

Kendall's au

As for a set of observations: $((x_1, y_1), (x_2, y_2), ..., (x_n, y_n))$:

- concordant: if both $x_i > x_j$ and $y_i > y_j$; or if both $x_i < x_j$ and $y_i < y_j$
- discordant: if $x_i > x_j$ and $y_i < y_j$ or $x_i < x_j$ and $y_i > y_j$

The kendall's τ coefficient is defined as:

$$\tau = \frac{n(concordant) - n(discordant)}{n(n-1)/2}$$

Kendall's au

It also can be writed as:

$$\tau = 4 \int \int F(x_1, x_2) dF(x_1, x_2) - 1 = 4 \int \int C(u_1, u_2) dC(u_1, u_2) - 1$$

The reparameterized Joe-Clayton copula

Joe-Calyton copula

$$\begin{split} & \textit{C}(\textit{u},\textit{v}|\theta,\delta) = \eta(\eta^{-1}(\textit{u}) + \eta^{-1}(\textit{v})) = 1 - [1 - \{(1 - \overline{\textit{u}}^{\theta})^{-\delta} + (1 - \overline{\textit{v}}^{\theta}) - 1\}^{-1/\delta}]^{1/\theta} \\ & \text{where } \eta(\textit{s}) = 1 - [1 - (1 + \textit{s})^{-1/\delta}]^{1/\theta}, \; \theta \geq 1, \; \delta \geq 0, \; \overline{\textit{u}} = 1 - \textit{u}, \; \text{and} \\ & \overline{\textit{v}} = 1 - \textit{v}. \end{split}$$

Tail-dependece

$$\lambda_L = 2^{-1/\delta}$$
 and $\lambda_U = 2 - 2^{1/ heta}$



The reparameterized Joe-Clayton copula

$$\tau = \begin{cases} 1 - 2/[\delta(2 - \theta)] + 4B(\delta + 2, 2/\theta - 1)/(\theta^2 \delta)1 \le \theta < 2\\ 1 - [\psi(2 + \delta) - \psi(1) - 1]/\delta\theta = 2\\ 1 - 2/[\delta(2 - \theta)] - 4\pi/[\theta^2 \delta(2 + \delta) \sin(2\pi\theta)B(1 + \delta + 2/\theta, 2 - 2/\theta)]\theta > \end{cases}$$
(1)

The reparameterized Joe-Clayton copula

Reparametrization

$$C(u, v | \lambda_L, \tau) = 1 - [1 - [[1 - \bar{u}^{\log 2/\log(t - \tau^{-1}(\lambda_L))}]^{\log 2/\log\lambda_L} + [1 - \bar{v}^{\log 2/\log(2 - \tau^{-1}(\lambda_L))} - 1]^{\log \lambda_L/\log 2}]^{\log(2 - \tau^{-1}(\lambda_L))/\log 2}$$

Where
$$\tau^{-1}(\lambda_L) = \lambda_U = 2 - 2^{1/\theta}$$

Covariate-dependent copula features

The covariate-dependent copula model that allows the copula features to be linked to the observed covariates:

$$au = \mathit{l}_{ au}^{-1}(oldsymbol{X}oldsymbol{eta}_{ au}) \qquad ext{and} \qquad \lambda = \mathit{l}_{\lambda}^{-1}(oldsymbol{X}oldsymbol{eta}_{\lambda})$$

- \bullet λ without subscripts represents the dependences in the lower or upper tails
- τ is Kendall's τ
- X is the set of covariates matrix
- ullet eta with subscripts is the corresponding coefficients vector
- $I_{\lambda}(\cdot)$ and $I_{\tau}(\cdot)$ are suitable *link function* that connect λ and τ with **X**

Marginal models

We assume the marginal models to be *split-t distributions*, then we allow the mean μ_k , the scale ϕ_k , the degree of freedom ν_k , the skewness κ_k of the split-t density in the kth to be linked to covariates:

$$\mu_k = \mathbf{X} \beta_{\mu k}, \nu_k = \exp(\mathbf{X} \beta_{\nu k});$$

$$\phi_k = \exp(\mathbf{X} \beta_{\phi k}), \kappa_k = \exp(\mathbf{X} \beta_{\kappa k})$$

where X_k is the covariate matrix in the kth margin

Covariates

Covariates(X_s)	Explanation
LastDay	the returns from yesterday
LastWeek	the returns from the previous five trading days
LastMonth	the returns from the previous twenty trading days
CloseAbs95	$(1-\rho)\sum_{s=0}^{\infty}\rho^{s} y_{t-2-s} $
CloseSqr95	$(1-\rho)\sum_{s=0}^{\infty} \rho^{s}(y_{t-2-s})^{2}$
MaxMin95	$(1-\rho)\sum_{s=0}^{\infty}\rho^{s}(Inp_{t-1-s}^{(h)}-Inp_{t-1-s}^{(f)})$

Table: Seven variables

Data generation

Crawling the following information:

- Company: JD and BABA
- source: https:caixin.com
- date: 2017/05/23 2018/08/17

News data preprocessing:

- Combine news data from the same day
- Combine weekend news data with next Monday news data
- Remove news data from weekend

Convert document into vector

Our model require the input to be represented as a fixed-length feature vector. One of the most common fixed-length features is bag-of-words. Despite their popularity, bag-of-words features have two major weaknesses:

- they lose the ordering of the words
- they ignore semantics of the words

So, we use **Doc2vec** to convert document into vectore. Then we can convert each document into a 200-dimensional vector. After that, the function umap() can help us to reduce the dimension of the vector to two dimensions.

Future work

Experiment	Covariate	Variable selected
1	one	None
2	X_s	Υ
3	X_s	N
4	X_n	Υ
5	X_n	N
6	$X_s + X_n$	Υ
7	$X_s + X_n$	N

Table: Experiment programe