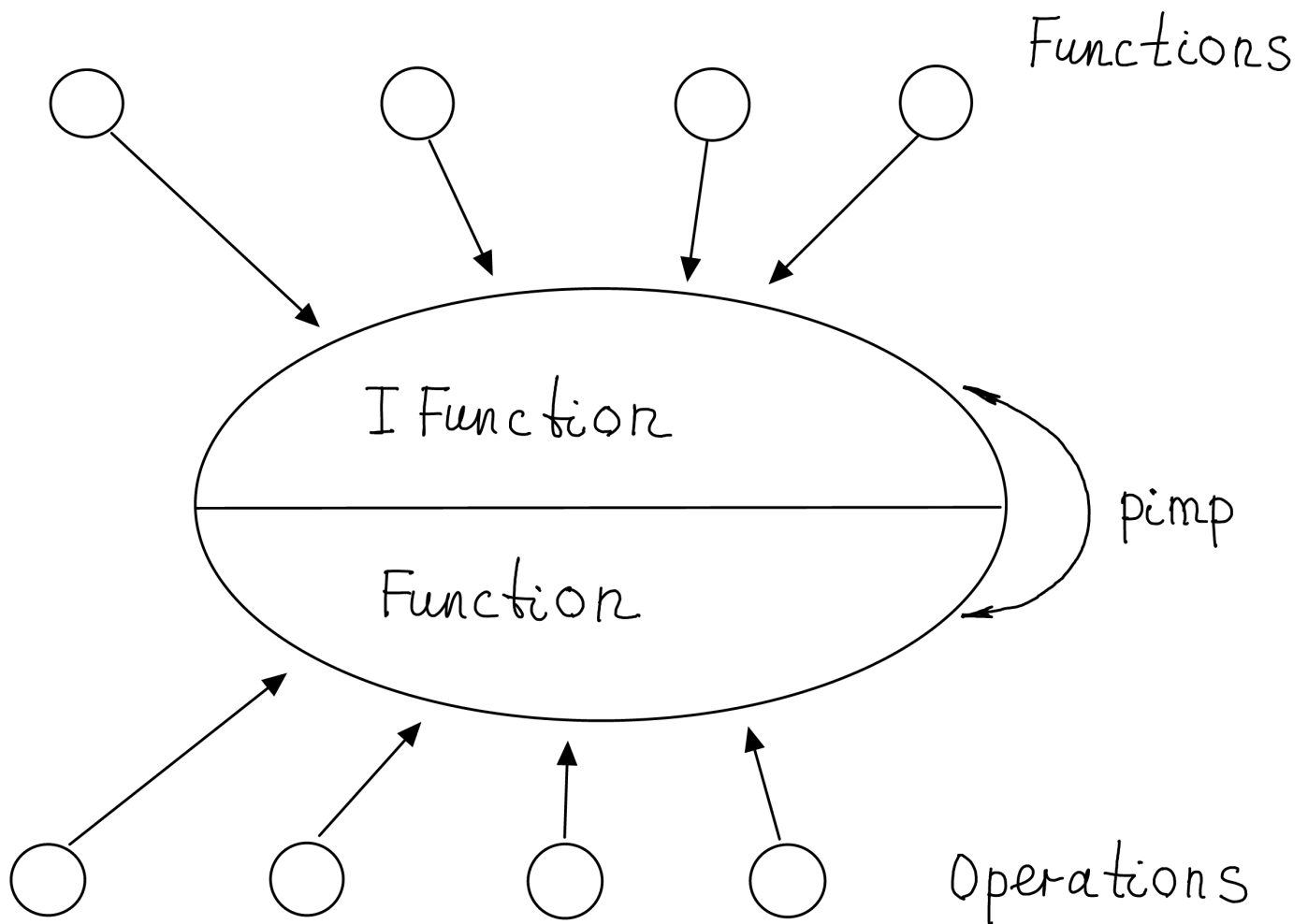


I: Construction of data curves
for financial models.

Design :



Methods :

- (a) Interpolation
- (b) least square fitting.

Data: Shape function for changes in yield curve in Hull-White model.

Inputs

$\lambda \geq 0$: the mean-reversion rate

t_0 : the initial time

Output: the function

$$\Gamma(t) = \frac{1 - \exp(-\lambda(t-t_0))}{\lambda(t-t_0)}, \quad t \geq t_0.$$

Domain: $[t_0, +\infty)$

Algorithm: given $t \geq t_0$ we define

$$F = \lambda(t-t_0)$$

if $(F < \varepsilon (\approx 10^{-8} \approx 1\text{cer}))$

{ return $\lim_{x \rightarrow 0} \frac{1 - \exp(-x)}{x} = 1$

}

// otherwise

$$\text{return } \frac{1 - \exp(-F)}{F}$$



Data: log-linear interpolation
of discount curve.

Inputs:

$(t_i)_{i=1, \dots, M}$: maturities, $t_{i+1} > t_i$.

$(d_i)_{i=1, \dots, M}$: discount factors.

t_0 : initial time, $t_0 < t_1$.

Output: discount curve $D = D(t)$
on $[t_0, t_M]$ obtained by
log-linear interpolation.

Domain: $[t_0, t_M]$

Algorithm:

Step 1: Compute the vectors of
& arguments: $\bar{x} = (t_0, \dots, t_M)$
values: $\bar{y} = (\underbrace{0}_{\log 1}, \log d_1, \dots, \log d_M)$

for linear interpolation.

Step 2: linear interpolation of
 $(\bar{x}, \bar{y}) \Rightarrow L(t), t \in [t_0, t_M].$

Step 3:

return $D(t) = \exp(L(t)), t \in [t_0, t_M].$



Data: least square fit in
Hull-White model.

Inputs:

$(t_i)_{i=1, \dots, M}$: maturities, $t_i < t_{i+1}$.

$(d_i)_{i=1, \dots, M}$: discount factors.

$\lambda \geq 0$: mean-reversion rate.

t_0 : initial time.

Output: the discount curve

$$D(t) = \exp(-\hat{A} \Gamma(t) (t - t_0)),$$
$$t \in [t_0, +\infty),$$

where

$$\Gamma(t) = \frac{1 - \exp(-\lambda (t - t_0))}{\lambda (t - t_0)}$$

is the shape of changes in yield
curve in Hull-White model and

$$\hat{A} = \arg \min_A \sum_{i=1}^M (\gamma_i - A \Gamma(t_i))^2$$

with the market yields

$$\gamma_i = - \frac{\log d_i}{t_i - t_0}, \quad i = 1, \dots, M.$$

Domain: $[t_0, +\infty)$

Algorithm:

Step 1: Compute the market yields:

$$\gamma_i = - \frac{\log d_i}{t_i - t_0}, \quad i = 1, \dots, M.$$

Step 2: Compute the values

$$\Gamma_i = \Gamma(t_i), \quad i = 1, \dots, M.$$

Step 3: Compute the constant \hat{A} from the least square fit:

$$\hat{A} = \arg \min_A \sum_{i=1}^M (\gamma_i - A \Gamma_i)^2$$

We deduce that

$$\hat{A} = \frac{\text{Cov}(\gamma, \Gamma)}{\text{Var}(\Gamma)},$$

where

$$\text{Cov}(\gamma, \Gamma) = \sum_{i=1}^M \gamma_i \Gamma_i,$$

$$\text{Var}(\Gamma) = \sum_{i=1}^M \Gamma_i^2.$$

Step 4

$$\text{return } D(t) = \exp\left(-\underbrace{\hat{A} \Gamma(t)}_{\text{yield}} (t - t_0)\right)$$

