

Web Search And Text Mining - A6
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Derivation 2.1

Please note that $\alpha = \mu$ in my derivation

The image shows a handwritten derivation of pagerank update equations on lined paper. The derivation is organized into two columns: 2.1 on the left and 2.2 on the right.

Column 2.1:

$$e_{ij} = \left(r_{ij} - \sum_{k \in K} p_{ik} q_{kj} \right)^2$$

$$\hat{p}_{ik} = p_{ik} + \frac{\alpha e_{ij}}{\partial p_{ik}}$$

$$\hat{q}_{kj} = q_{kj} + \frac{\alpha e_{ij}}{\partial q_{kj}}$$

$$\frac{\partial e_{ij}}{\partial p_{ik}} = \frac{\partial \left(r_{ij} - \sum_{k \in K} p_{ik} q_{kj} \right)^2}{\partial p_{ik}}$$

$$= -2 \left(r_{ij} - \sum_{k \in K} p_{ik} q_{kj} \right) q_{kj}$$

Similarity,

$$\frac{\partial e_{ij}}{\partial q_{kj}} = \frac{\partial \left(r_{ij} - \sum_{k \in K} p_{ik} q_{kj} \right)^2}{\partial q_{kj}}$$

$$= -2 \left(r_{ij} - \sum_{k \in K} p_{ik} q_{kj} \right) p_{ik}$$

$\therefore \hat{p}_{ik} = p_{ik} + 2\alpha \left(r_{ij} - \sum_{k \in K} p_{ik} q_{kj} \right) q_{kj}$

$\therefore \hat{q}_{kj} = q_{kj} + 2\alpha \left(r_{ij} - \sum_{k \in K} p_{ik} q_{kj} \right) p_{ik}$

Derivation 2.2

Please note that $\alpha = \mu$ and $\beta = \lambda$ in my derivation

$$\text{2.2. } e_{ij} = (r_{ij} - \sum_{K \in K} p_{ik} \alpha_{kj})^2 + \lambda \left(\sum_{K \in K} p_{ik}^2 + \sum_{K \in K} \alpha_{kj}^2 \right)$$
$$\frac{\partial e}{\partial p_{ik}} = -2(r_{ij} - \sum_{K \in K} p_{ik} \alpha_{kj}) \alpha_{kj} + 2\lambda p_{ik}$$
$$\frac{\partial e}{\partial \alpha_{kj}} = -2(r_{ij} - \sum_{K \in K} p_{ik} \alpha_{kj}) p_{ik} + 2\lambda \alpha_{kj}$$
$$\hat{p}_{ik} = p_{ik} + 2 \left[(r_{ij} - \sum_{K \in K} p_{ik} \alpha_{kj}) \alpha_{kj} - \lambda p_{ik} \right]$$
$$\hat{\alpha}_{kj} = \alpha_{kj} + 2 \left[(r_{ij} - \sum_{K \in K} p_{ik} \alpha_{kj}) p_{ik} - \lambda \alpha_{kj} \right]$$

Cross Validation Tables

RMSE	$\lambda = 0.005$	$\lambda = 0.1$	$\lambda = 0.5$
$\mu = .0001$	0.9130	0.9139	0.9459
$\mu = .0005$	0.9134	0.9142	0.9461
$\mu = .001$	0.9136	0.9147	0.9467

Table 1: $r = 1$

RMSE	$\lambda = 0.005$	$\lambda = 0.1$	$\lambda = 0.5$
$\mu = .0001$	0.8958	0.8930	0.9354
$\mu = .0005$	0.9024	0.8949	0.9311
$\mu = .001$	0.9057	0.8969	0.9311

Table 2: $r = 3$

RMSE	$\lambda = 0.005$	$\lambda = 0.1$	$\lambda = 0.5$
$\mu = .0001$	0.9102	0.8960	0.9329
$\mu = .0005$	0.9196	0.9013	0.9301
$\mu = .001$	0.9220	0.9003	0.9305

Table 3: $r = 5$

μ	0.0001
λ	0.1
r	3
RMSE	0.8930

Table 4: $r = 5$

Analysis

- What do you observe when you vary r ? Why?

There is a variation in RMSE. For most combinations of λ and μ , RMSE decreases from $r=3$ and then increases for $r=5$ but is still smaller than for $r=1$.

Though intuitively it might seem that increasing the number of latent features(r), the results should improve, it is quite contrary. Gradual increase with r is justified but after a point, with further increase in r , the learner starts to overfit and thus performs poorly on the test data. Though experiment wasn't carried out to check the training error, it is expected to decrease with r .

- Which model is the best? Please describe the best model in Table 4 and explain your choice.

The best model is which results in the lowest cross validation Root Mean Squared Error. This model in our combinations of parameters is with $r=3$, $\lambda = 0.1$ and $\mu = 0.0001$. The RMSE is 0.8930.

3. Suppose you are using regularized MF in real systems, how will you choose parameters? Why?

In real system with real data, I would carry out a similar experiment to calculate cross validation RMSE for different sets of parameters. I would chose a much larger suite of parameters and the final model will be the one with the lowest RMSE. Also, due to a larger set of data and large number of experiments, methods to parallelize the entire process will be useful.