MTA SZTAKI datamining search

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Using Combination and Segmentation for automatic concept detection

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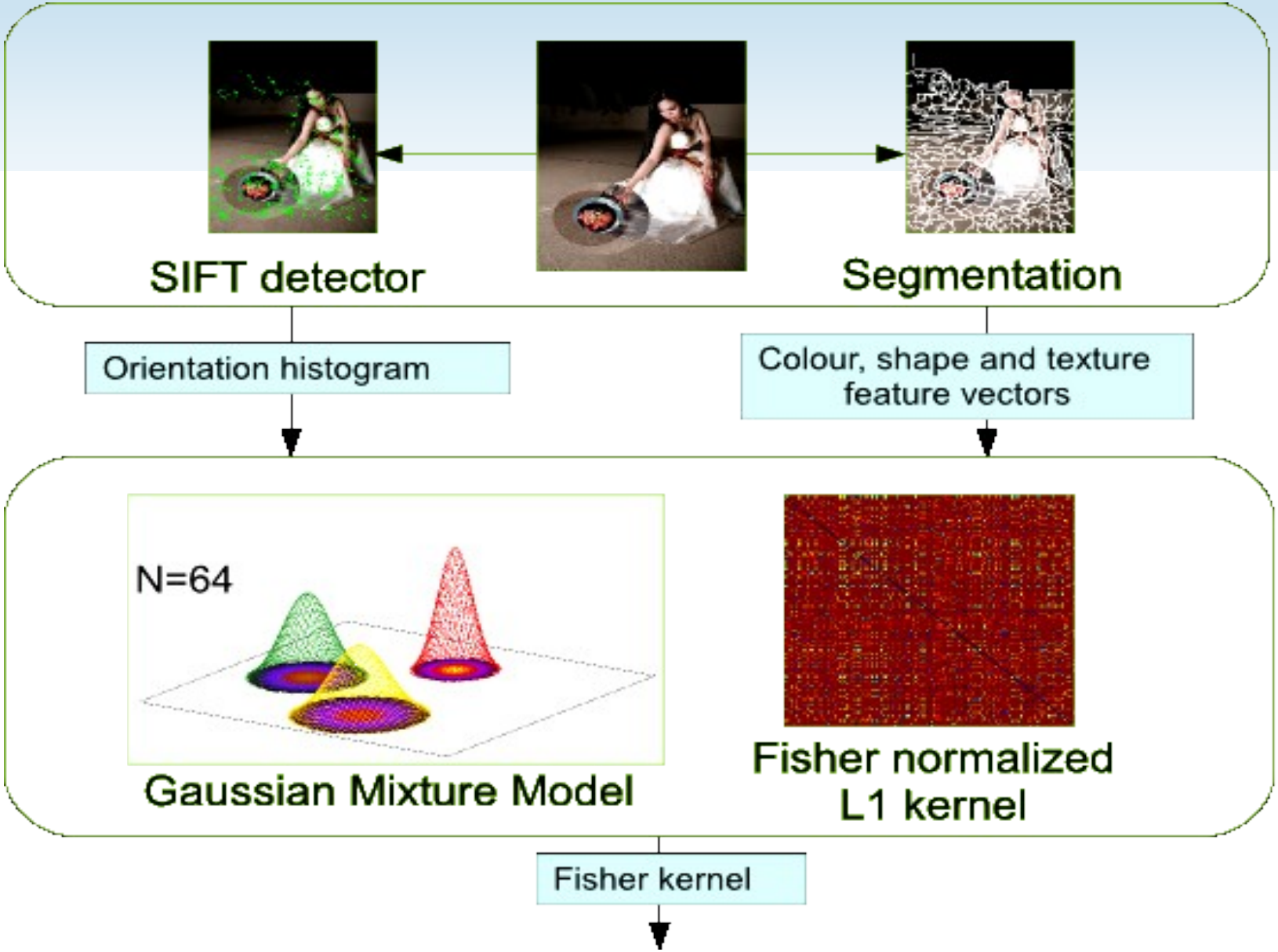
Flowchart of the processing



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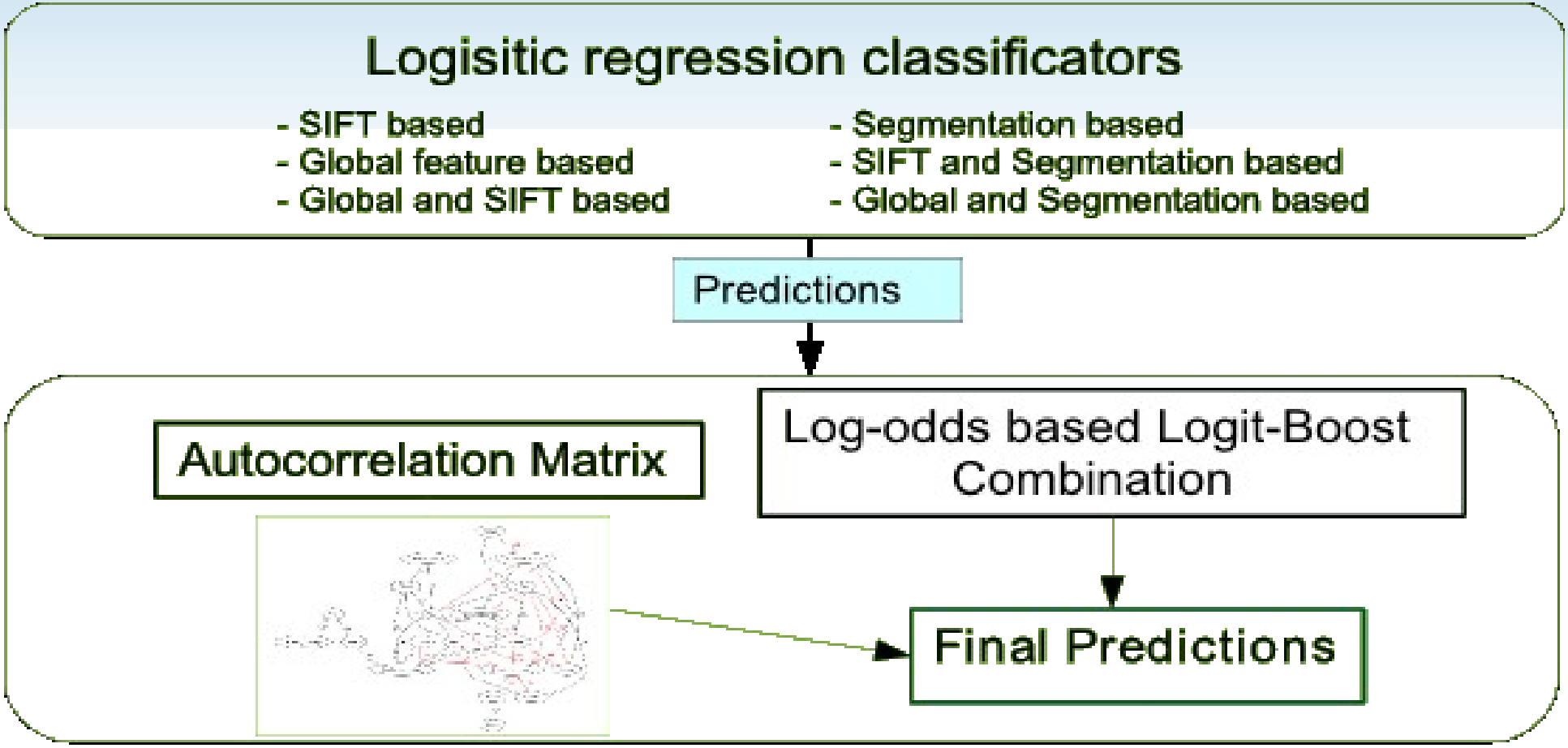


Final results

	EER	AUC
SIFT + Segmentation + Cross	0.291718	0.773133
SIFT + Segmentation	0.296315	0.771324
Log Odds combination	0.304113	0.746300
SIFT	0.322632	0.733264
Segmentation	0.346106	0.707860

Final results

Nr.	Concept	AUC	AUC comb.	LogOdds c.	Nr.	Concept	AUC	AUC comb.	LogOdds c.
0	Partylife	0.73957	0.72941	0.68350	27	Day	0.74645	**0.76309**	**0.76555**
1	Familiy_Friends	0.73815	0.73811	0.71786	28	Night	0.86187	0.86187	**0.87458**
2	Beach_Holidays	0.81424	**0.85588**	0.79171	29	No_Visual_Time	0.74712	**0.75651**	0.74943
3	Building_Sights	0.80933	0.80933	0.79170	30	Sunny	0.72356	**0.73187**	0.72782
4	Snow	0.80294	0.75331	0.79255	31	Sunset_Sunrise	0.92588	0.92588	0.92026
5	Citylife	0.78624	0.78624	0.75672	32	Canvas	0.73779	0.73779	0.73235
6	Landscape_Nature	0.89293	0.89293	0.88607	33	Still_Life	0.74807	**0.75257**	0.72224
7	Sports	0.59259	**0.59820**	0.51282	34	Macro	0.70740	0.70740	0.69002
8	Desert	0.83242	0.83242	0.74518	35	Portrait	0.77825	0.77825	0.73150
9	Spring	0.75002	0.75002	0.68572	36	Overexposed	0.76191	0.76191	0.72049
10	Summer	0.77211	**0.77541**	0.73943	37	Underexposed	0.86044	0.86044	**0.88017**
11	Autumn	0.77894	0.77894	0.73783	38	Neutral_Illumination	0.79114	0.79114	**0.79946**
12	Winter	0.79843	0.79843	**0.80648**	39	Motion_Blur	0.66064	0.66064	0.62978
13	No_Visual_Season	0.76659	0.75141	0.69890	40	Out_of_focus	0.79453	0.74420	0.72747
14	Indoor	0.72815	0.69309	0.71512	41	Partly_Blurred	0.82296	0.82296	0.78099
15	Outdoor	0.81166	0.80824	0.80551	42	No_Blur	0.79566	0.79566	0.73280
16	No_Visual_Place	0.72283	0.72283	0.64580	43	Single_Person	0.71757	0.71757	0.62987
17	Plants	0.78703	**0.79857**	0.78064	44	Small_Group	0.66305	0.66305	0.66832
18	Flowers	0.79807	**0.81733**	**0.80806**	45	Big_Group	0.78595	0.78595	0.72330
19	Trees	0.82024	**0.83775**	**0.85227**	46	No_Persons	0.72840	0.72840	0.72431
20	Sky	0.87776	0.87776	0.85901	47	Animals	0.74320	0.74320	0.70871
21	Clouds	0.88680	**0.89788**	0.88929	48	Food	0.83345	**0.84414**	0.83605
22	Water	0.80937	0.80937	0.79304	49	Vehicle	0.72292	**0.73282**	0.70768
23	Lake	0.79240	**0.85950**	0.73959	50	Aesthetic_Impression	0.63817	0.63817	0.62796
24	River	0.74148	0.74148	0.70190	51	Overall_Quality	0.63330	0.63330	0.55105
25	Sea	0.87256	**0.89580**	0.87399	52	Fancy	0.56859	0.56859	0.52613
26	Mountains	0.85911	0.85911	0.85493					
	mean AUC	**0.7713**	**0.7731**	**0.7463**		**Mean increase:**		**0.0018**	**-0.0250**

Feature extraction

Graph based Segmentation

- Undirected weighted graph over neighboring pixels
- Bottom-up clustering with dynamic thresholds
- Sobel gradient image to select important edges

Local features

- SIFT descriptors

Feature extraction: vectors

From graph based segmentation

Average RGB HSV	RGB, HSV Histogram	Contrast

Zig-Zag Fourier

From local feature points

128 SIFT descriptor

The modeling: Fisher vectors

Bag of visual words. Images are represented by gradient vector of a generative probability model (GMM) [Perronnin, Dance.]

Fitting a GMM with parameters $\Phi = \{w_i, \mu_i, \Sigma_i,\ i = 1 \ldots N\}$

Gradient of the log-likelihood describes the direction in which parameters should be modified to best fit the data:

$$\nabla_\Phi \log p(I|\Phi)$$

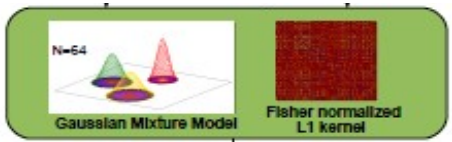
Fisher vector (normalized):

$$\mathbf{f}_I = F_\Phi^{-1/2} \nabla_\Phi \log p(I|\Phi)$$

$$F_\Phi = E_X P\left[\nabla_\Phi \log p(I|\Phi) \nabla_\Phi \log p(I|\Phi)^T\right]$$

Input to the classifier:

$$K(\mathbf{f}_I, \mathbf{f}_J) = \sum_{t=1}^{T} ||\tilde{\mathbf{f}}_I - \tilde{\mathbf{f}}_t||_1 \cdot ||\tilde{\mathbf{f}}_J - \tilde{\mathbf{f}}_t||_1$$



Classification

Logistic regression based classifier

- Computed for each concept using the Liblinear package

Combining the results of the different concepts

- *Method 1*: log odds-logitBoost
- *Method 2*: exploiting information embedded in training annotation labels

Combining 1

Log odds based combining

Log odds features: computes new features from the outputs of the different classificators. Creates a new re-reanking of results.

Boosting based learning on the re-ranked results

	EER	AUC
SIFT + Segmentation + Cross	0.291718	0.773133
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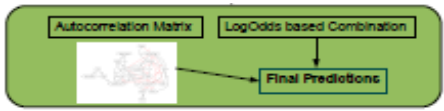
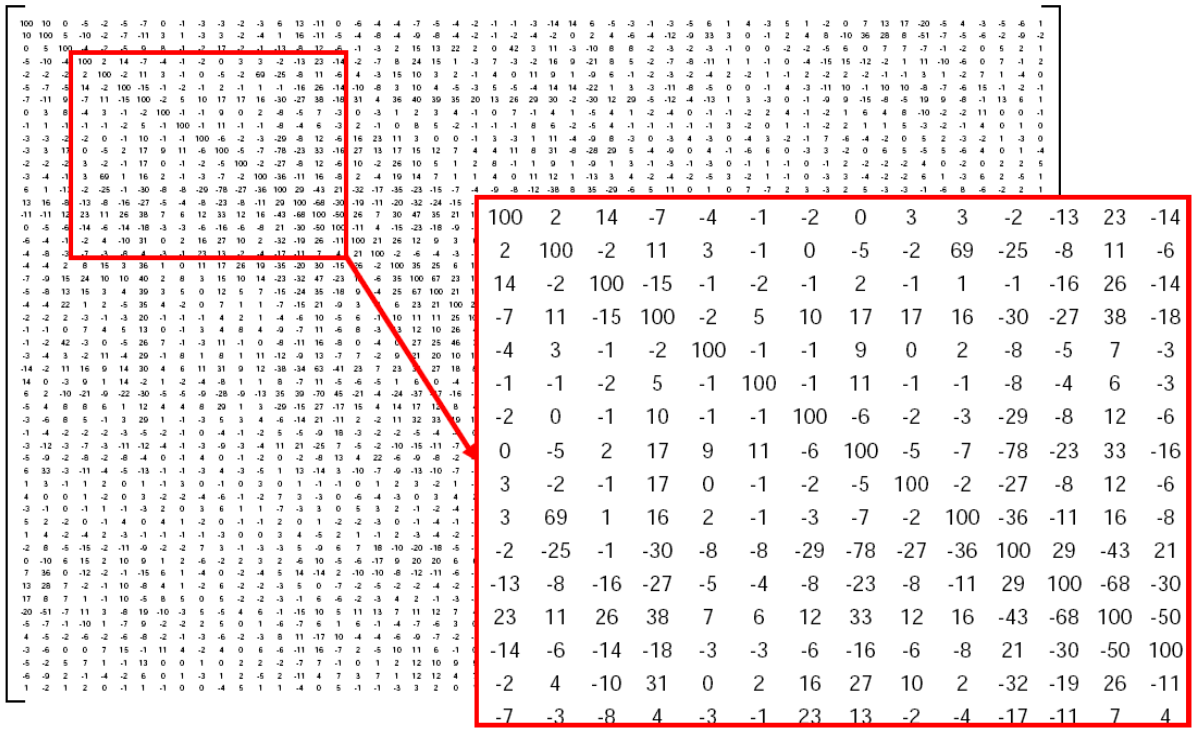


Combining 2

Correlation matrix from training annotations

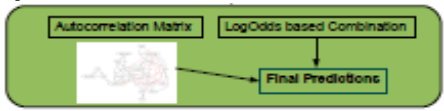
0 Partylife
1 Familiy_Friends
2 Beach_Holidays
3 Building_Sights
4 Snow
5 Citylife
6 Landscape_Nature
7 Sports
8 Desert
9 Spring
10 Summer
11 Autumn
12 Winter
13 No_Visual_Season
14 Indoor
15 Outdoor
16 No_Visual_Place
17 Plants
18 Flowers
19 Trees
20 Sky
21 Clouds
22 Water
23 Lake
24 River
25 Sea
26 Mountains
27 Day
28 Night
29 No_Visual_Time
30 Sunny
31 Sunset_Sunrise
32 Canvas
33 Still_Life
34 Macro
35 Portrait
36 Overexposed
37 Underexposed
38 Neutral_Illumination
39 Motion_Blur
40 Out_of_focus

C =



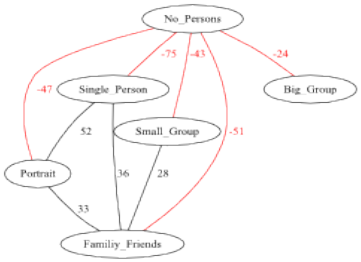
c_{ij} = corr (a_i; a_j), a_i is the ith column of A,

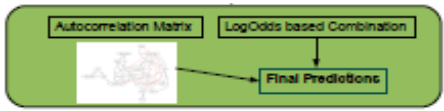
corr (x; y) = cov (x; y) = (std (x) std (y))



Combining 2

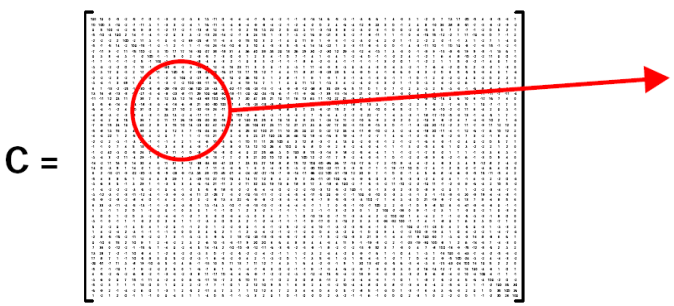
Correlation matrix from training annotations represented as a graph

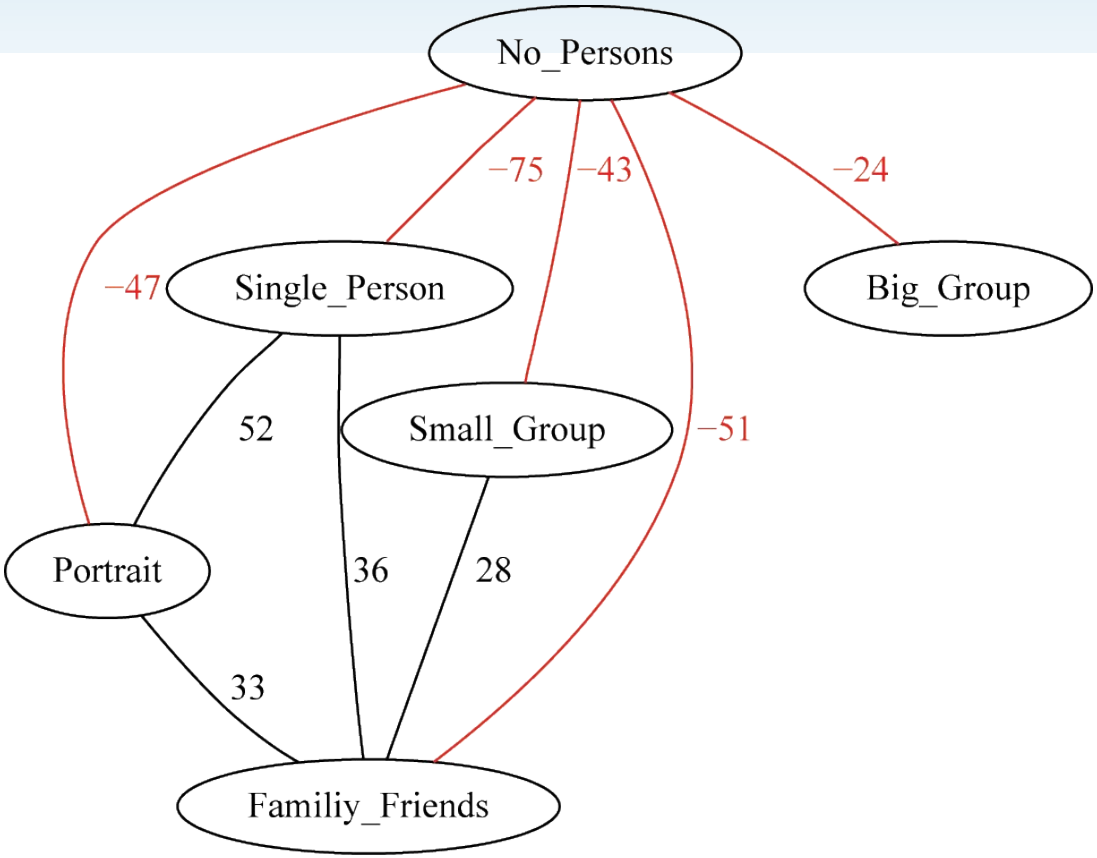


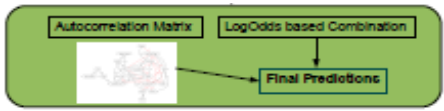


Combining 2

Correlation matrix subgraph







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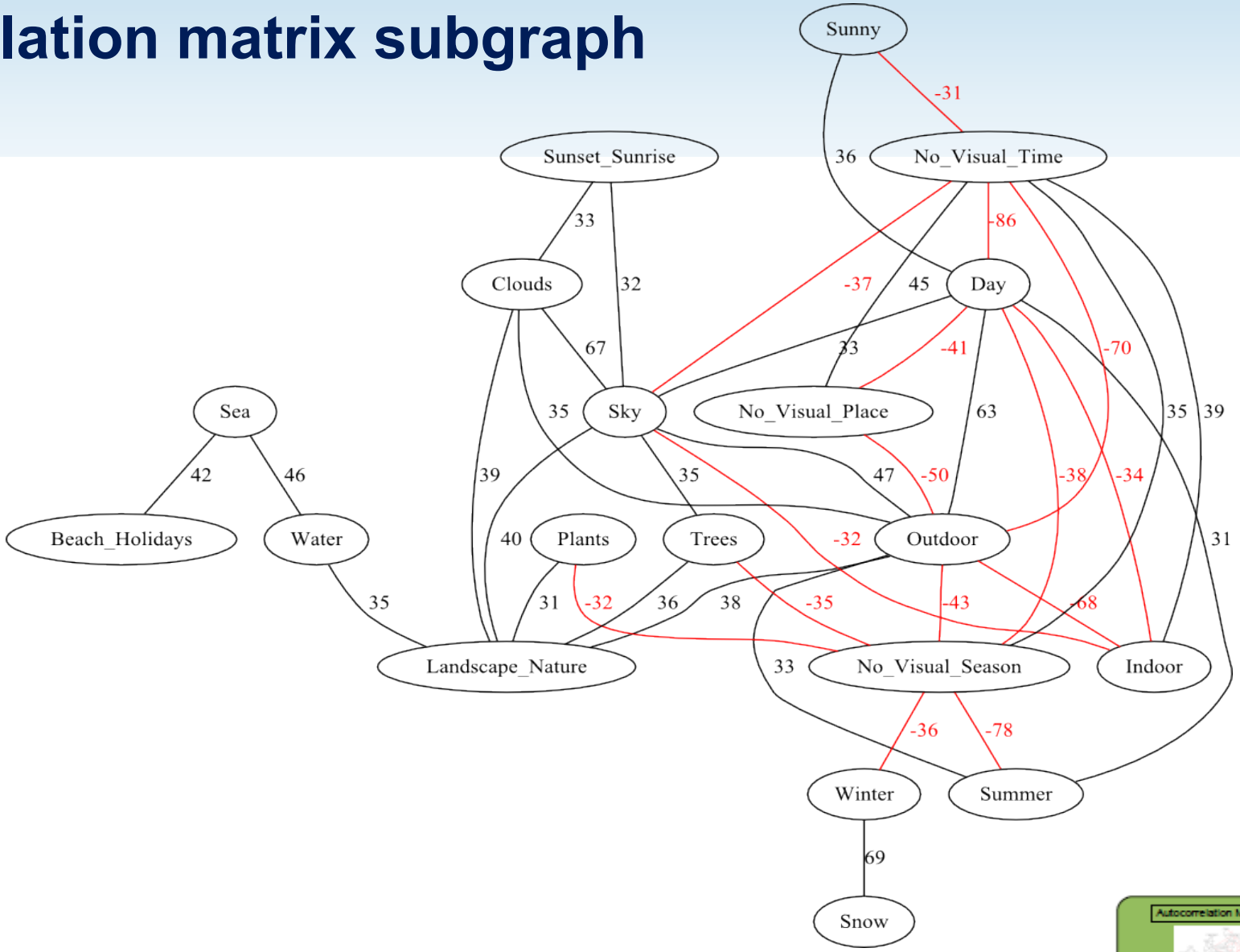

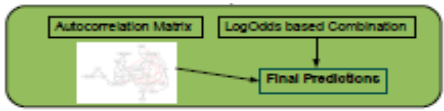

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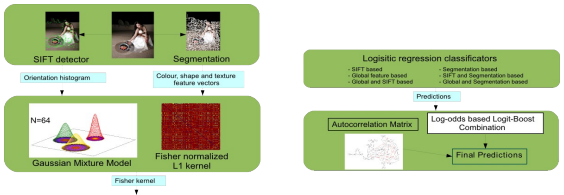
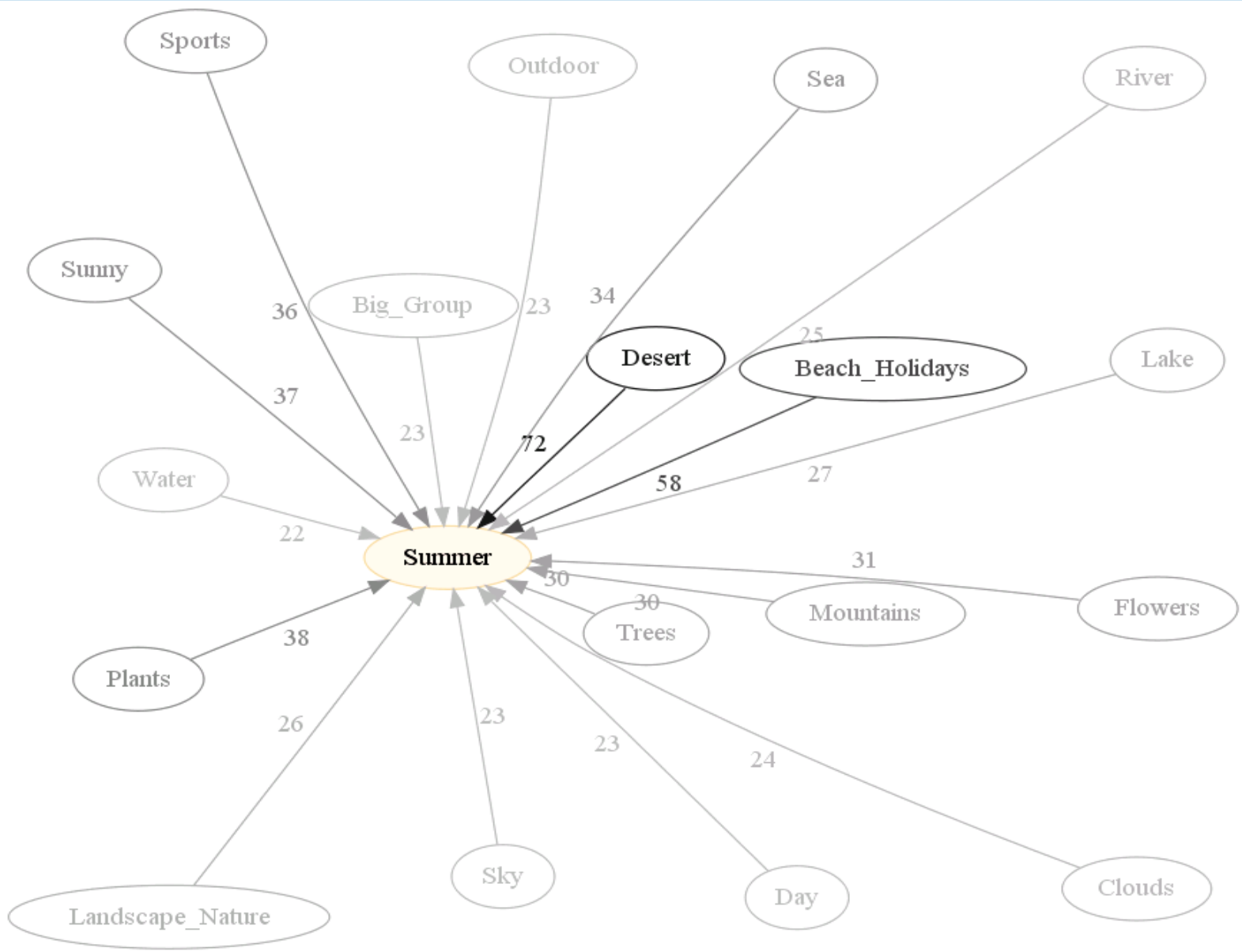


What more is in annotations?



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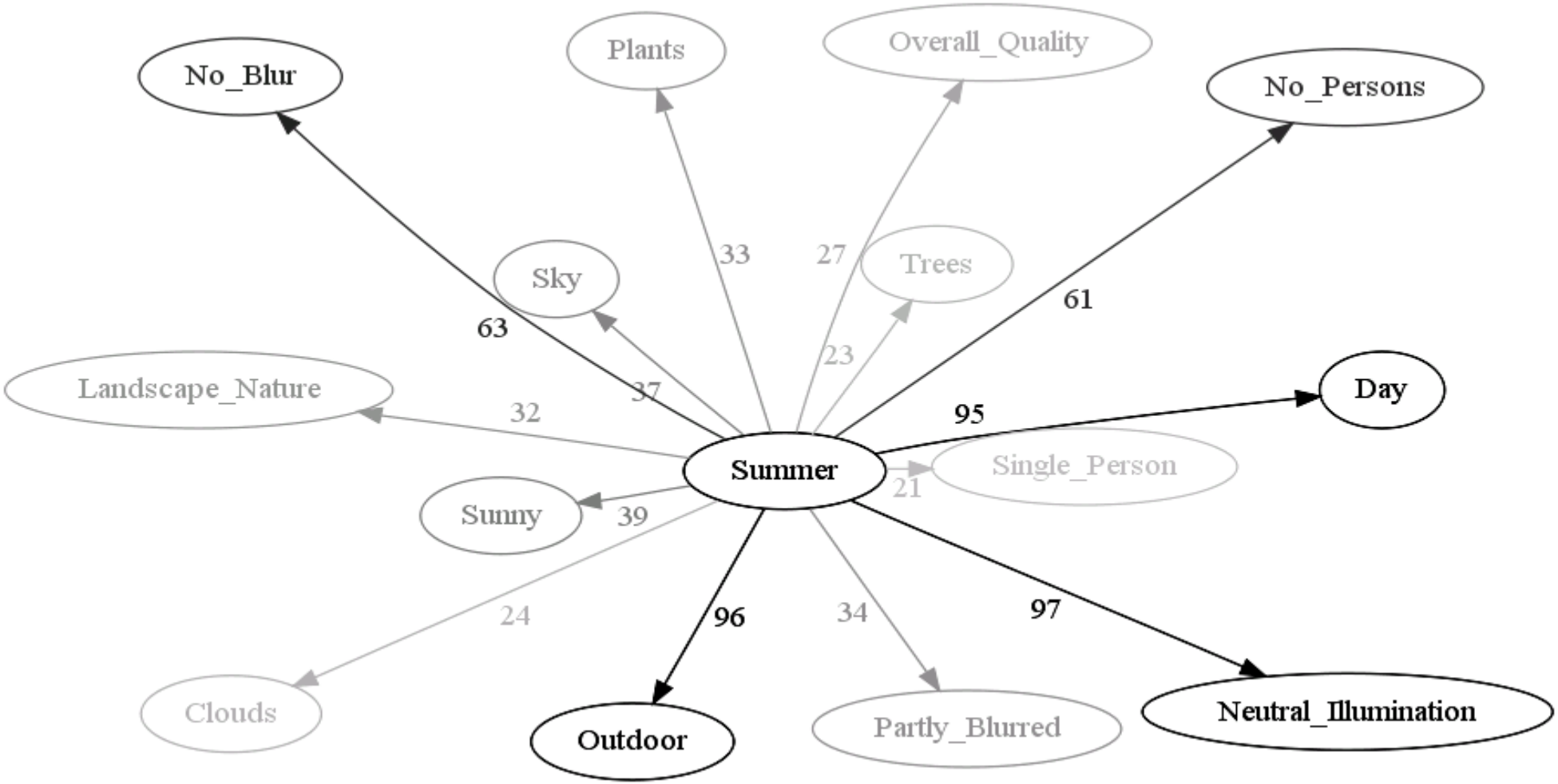

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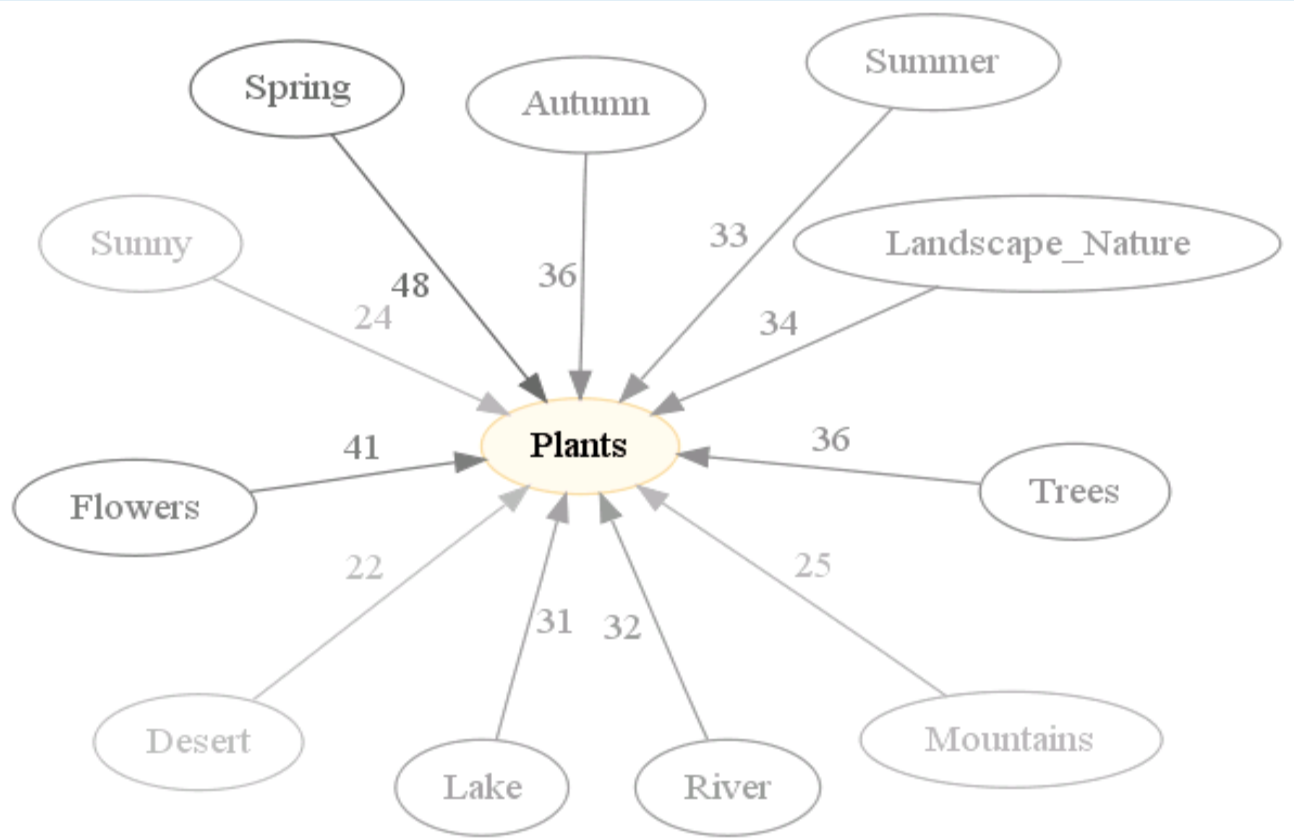

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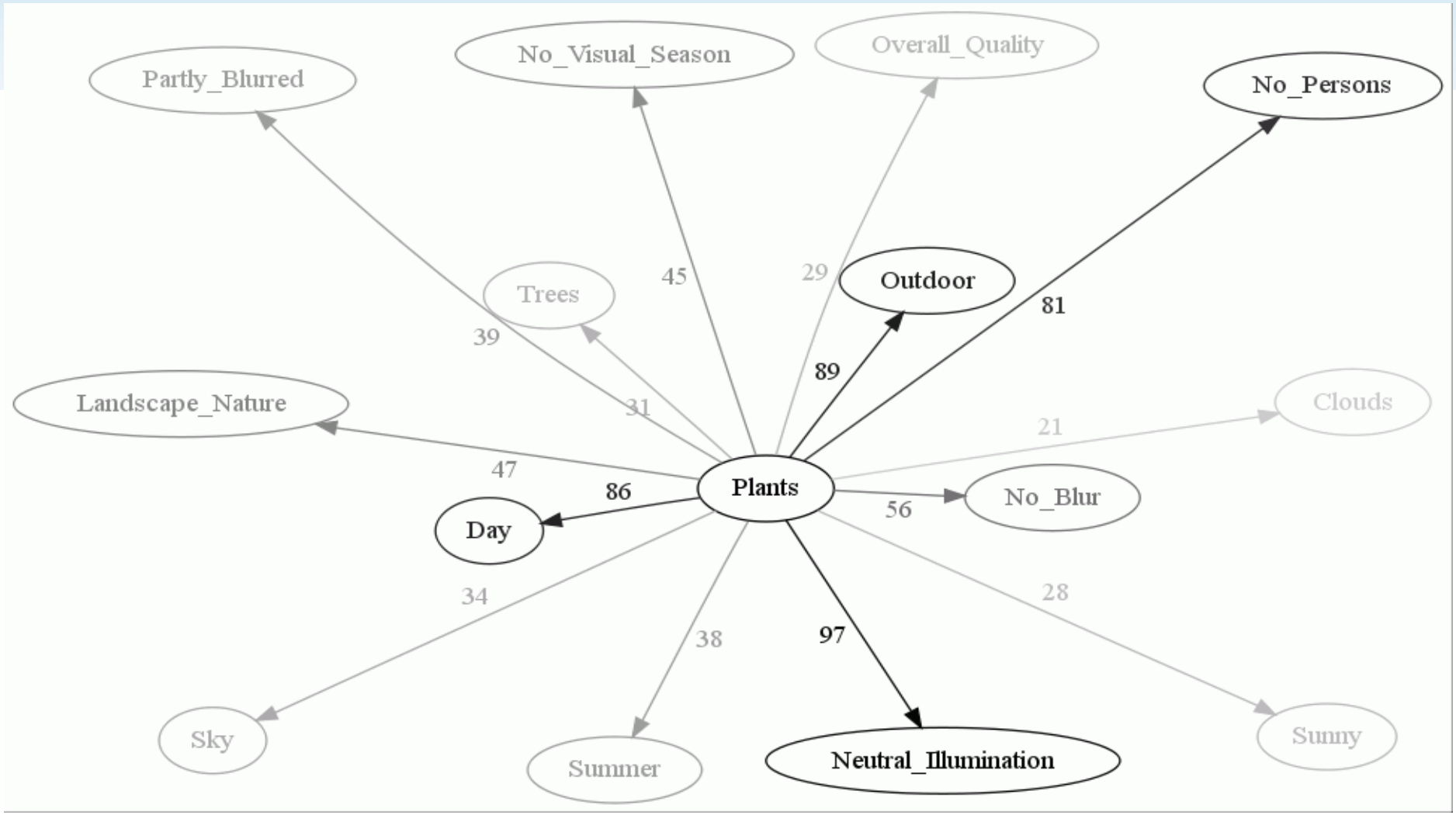
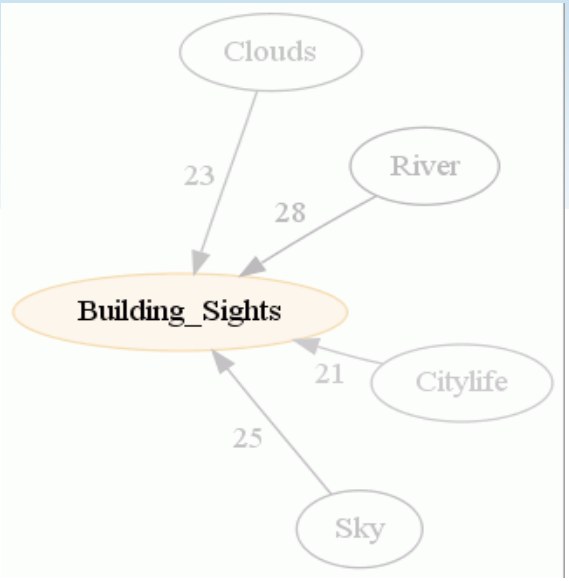
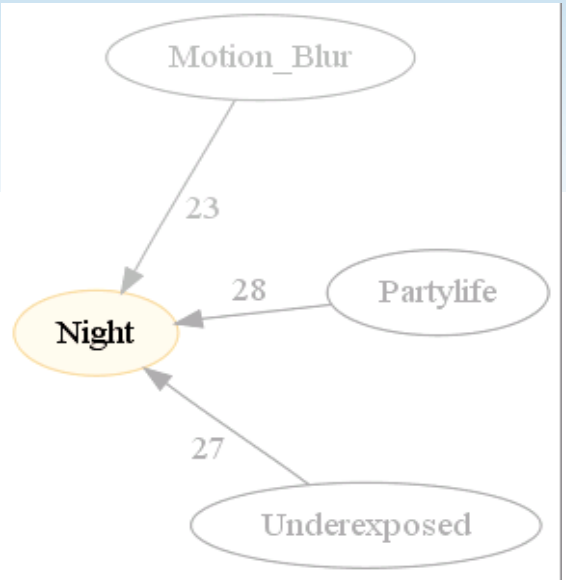
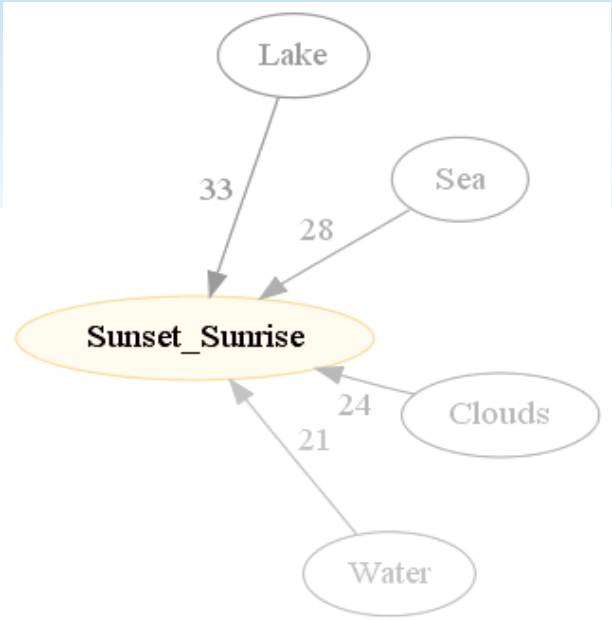
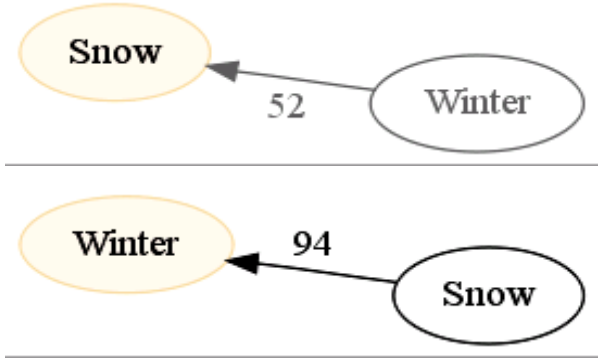


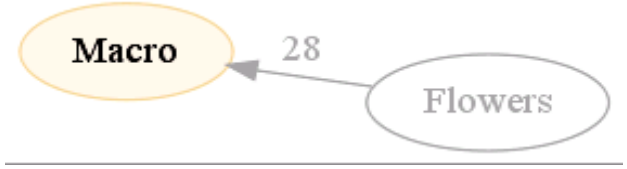
Thank You!











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