WINE NOT?

USING NLP TO EXPLORE FLAVOR PROFILES IN WINE REVIEWS

GENEVIEVE MCGUIRE

SOMM BACKGROUND…

Goal: Develop a tool useful for both sommeliers and casual wine drinkers

THE WORKFLOW

DATA

WineEnthusiast Magazine reviews from 2017

130k data points

CLEANING

Domain stop words

Lemmatization

Remove hapaxes

VECTORIZER

CountVectorizer

TF-IDF

LSA & LDA

TruncatedSVD

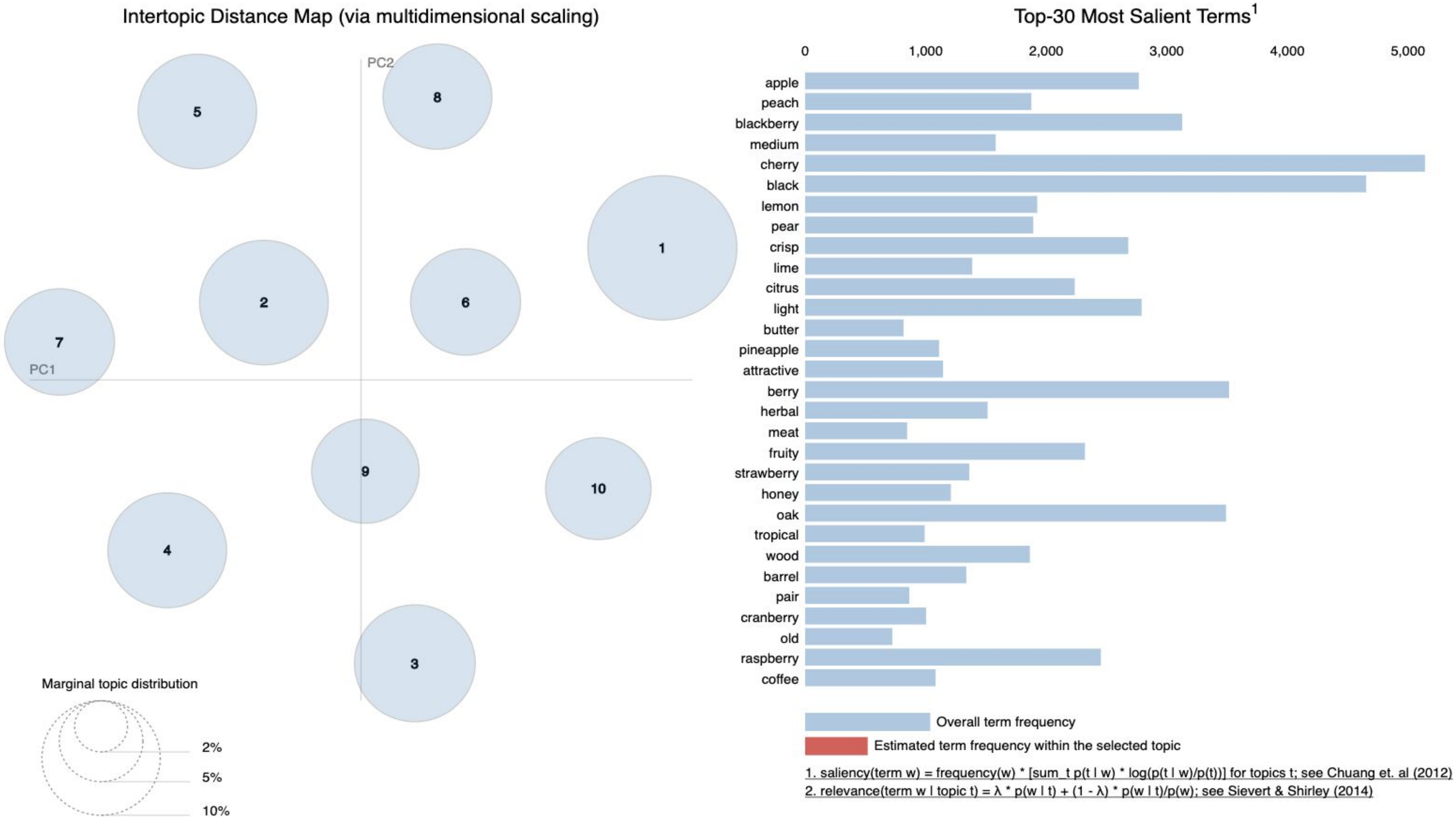
NMF

LDA: Gensim & Sklearn

kaggle™

NMF TOPICS

	1	2	3	4	5	6	7	8	9	10
RED	black cherry pepper spice licorice		ripe rich structure wood balance	red fruity	soft cherry raspberry	dry tannic core herb		blackberry dark chocolate blend tannic	body light medium color	berry plum herbal spice earthy
ROSE				fruity bright fresh currant	sweet simple cherry raspberry	dry			strawberry light	
WHITE		apple citrus white lemon crisp		bright fresh	sweet	dry bone herb	oak vanilla toast barrel butter			



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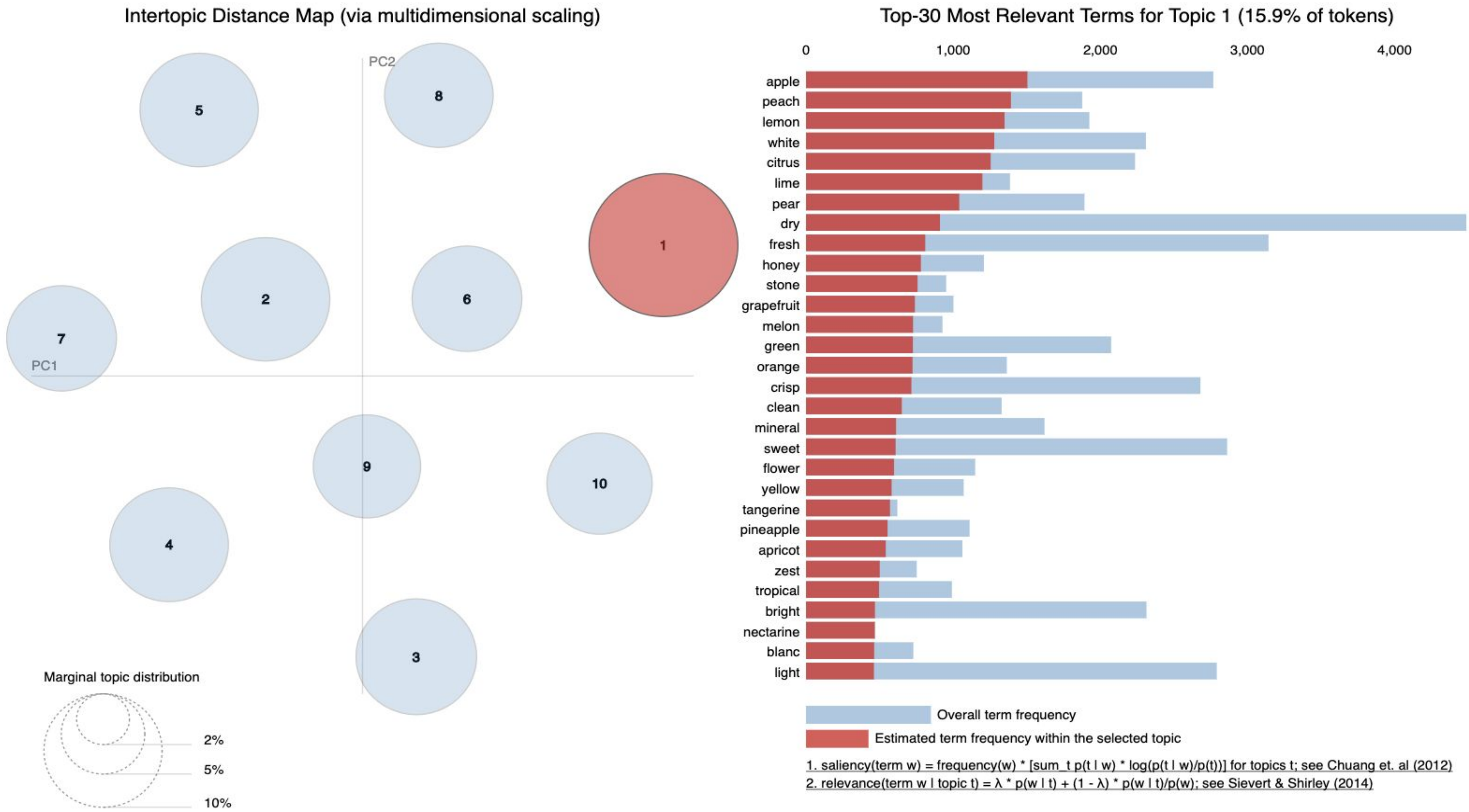
2. relevance(term w | topic t) = λ * p(w | t) + (1 - λ) * p(w | t)/p(w); see Sievert & Shirley (2014)



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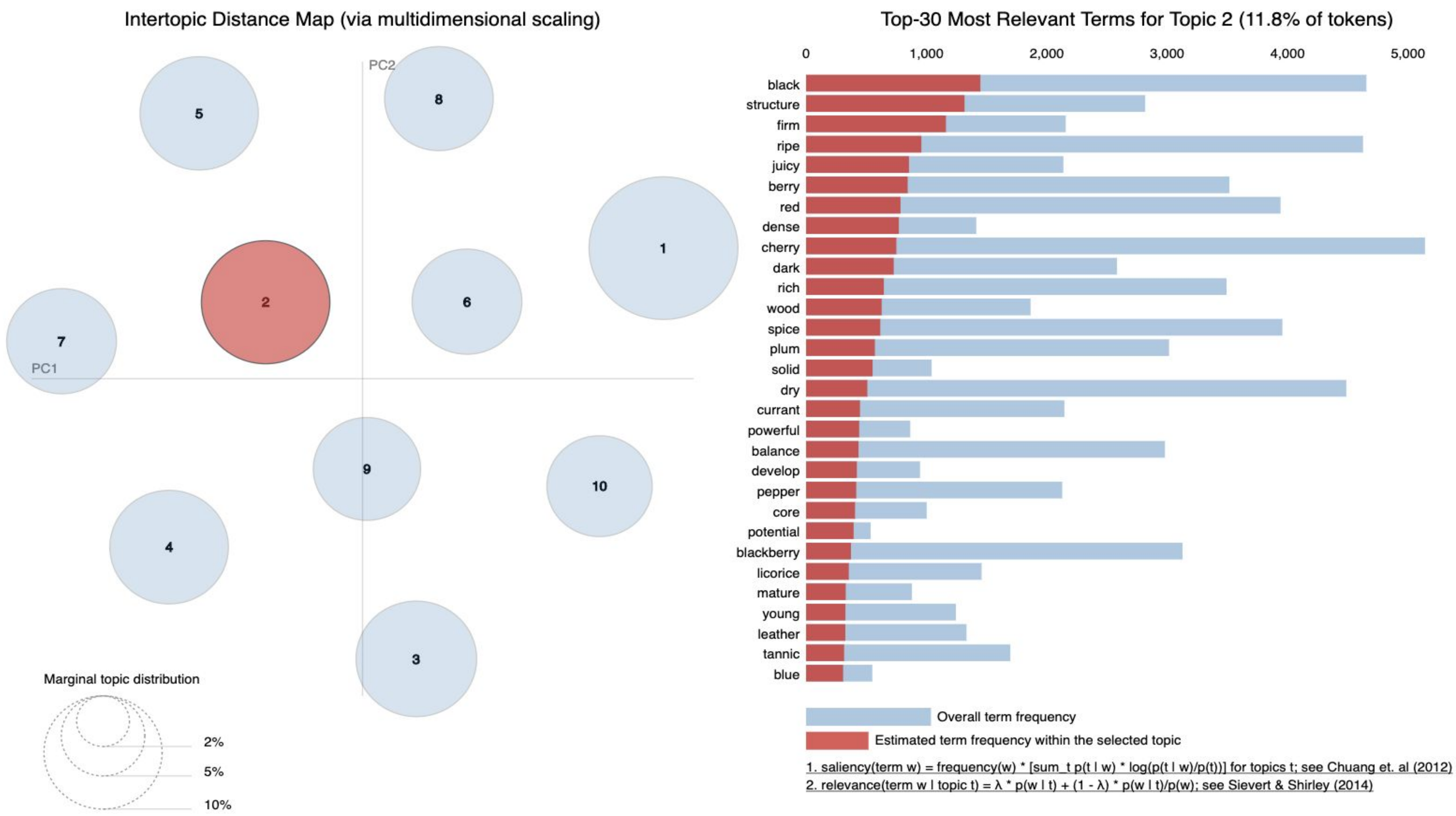

Intertopic Distance Map (via multidimensional scaling)

Top-30 Most Relevant Terms for Topic 2 (11.8% of tokens)

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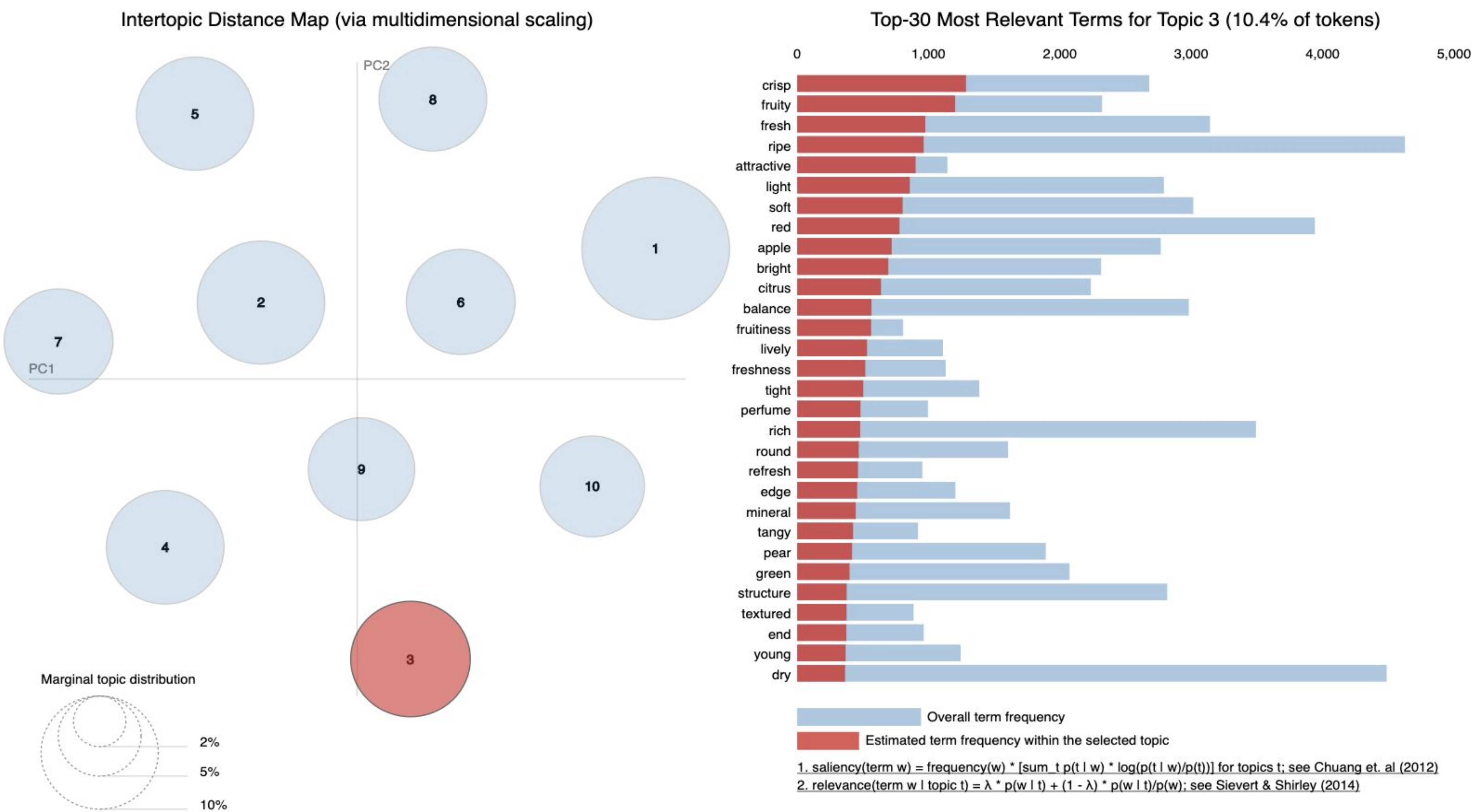

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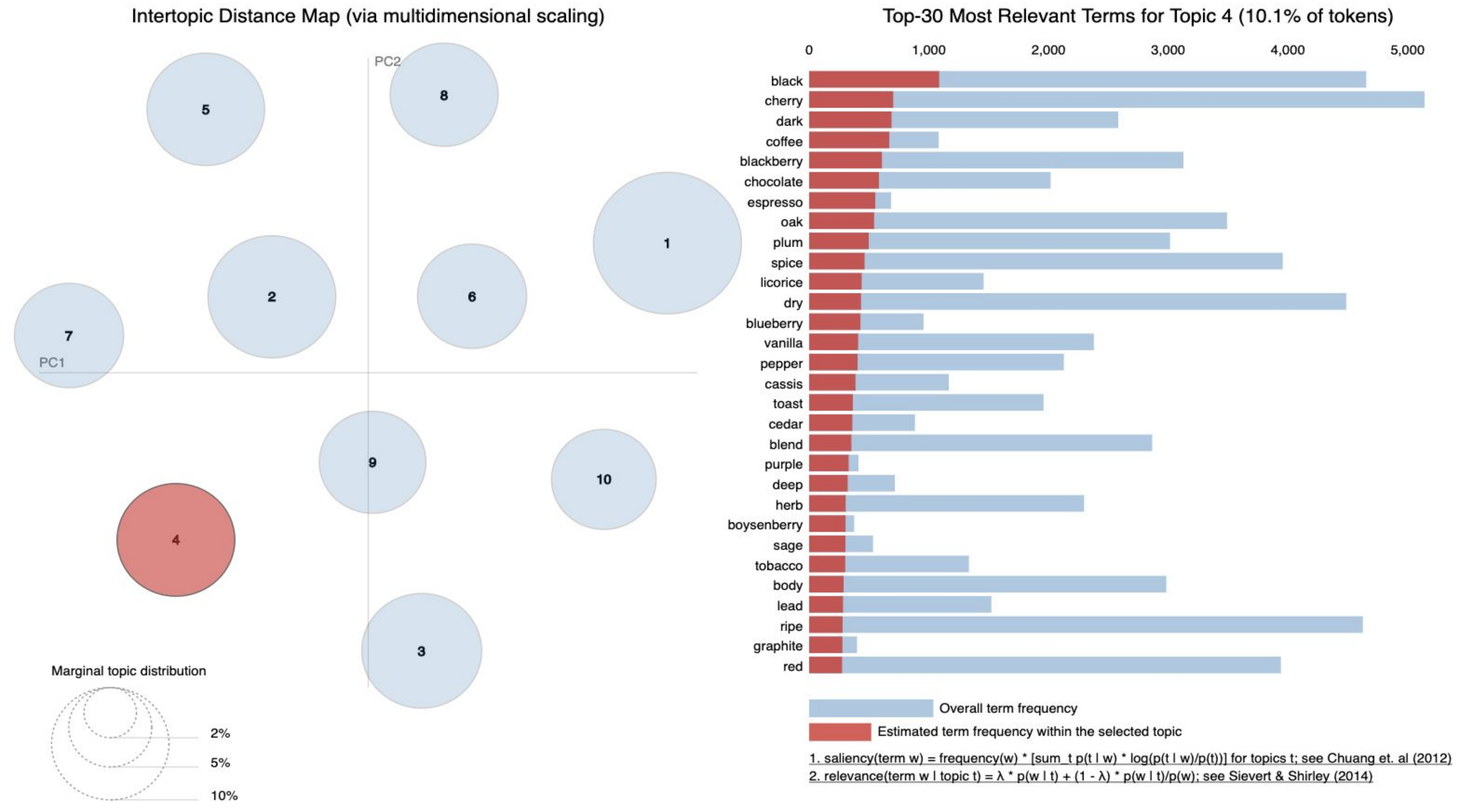

Intertopic Distance Map (via multidimensional scaling)

Top-30 Most Relevant Terms for Topic 4 (10.1% of tokens)

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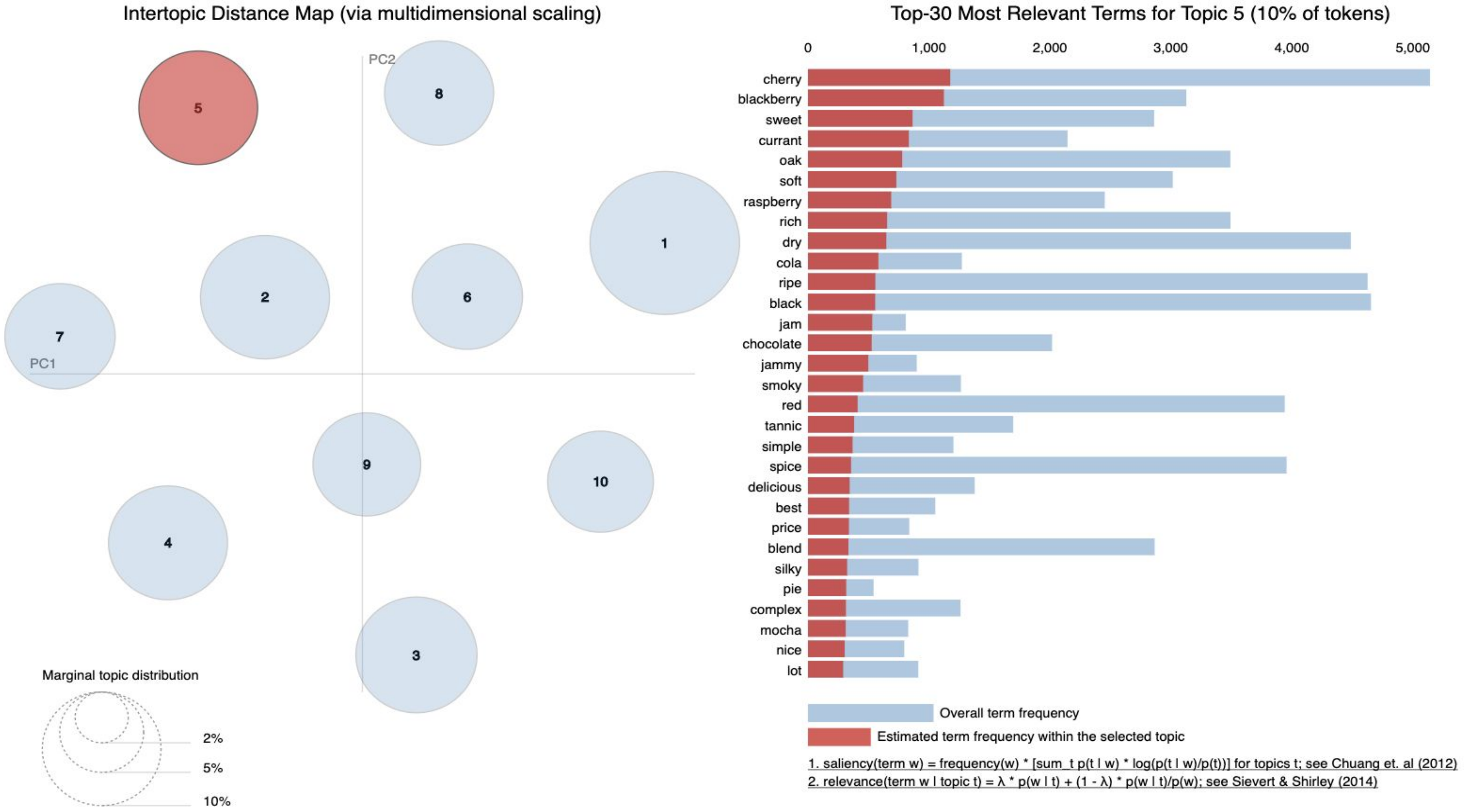

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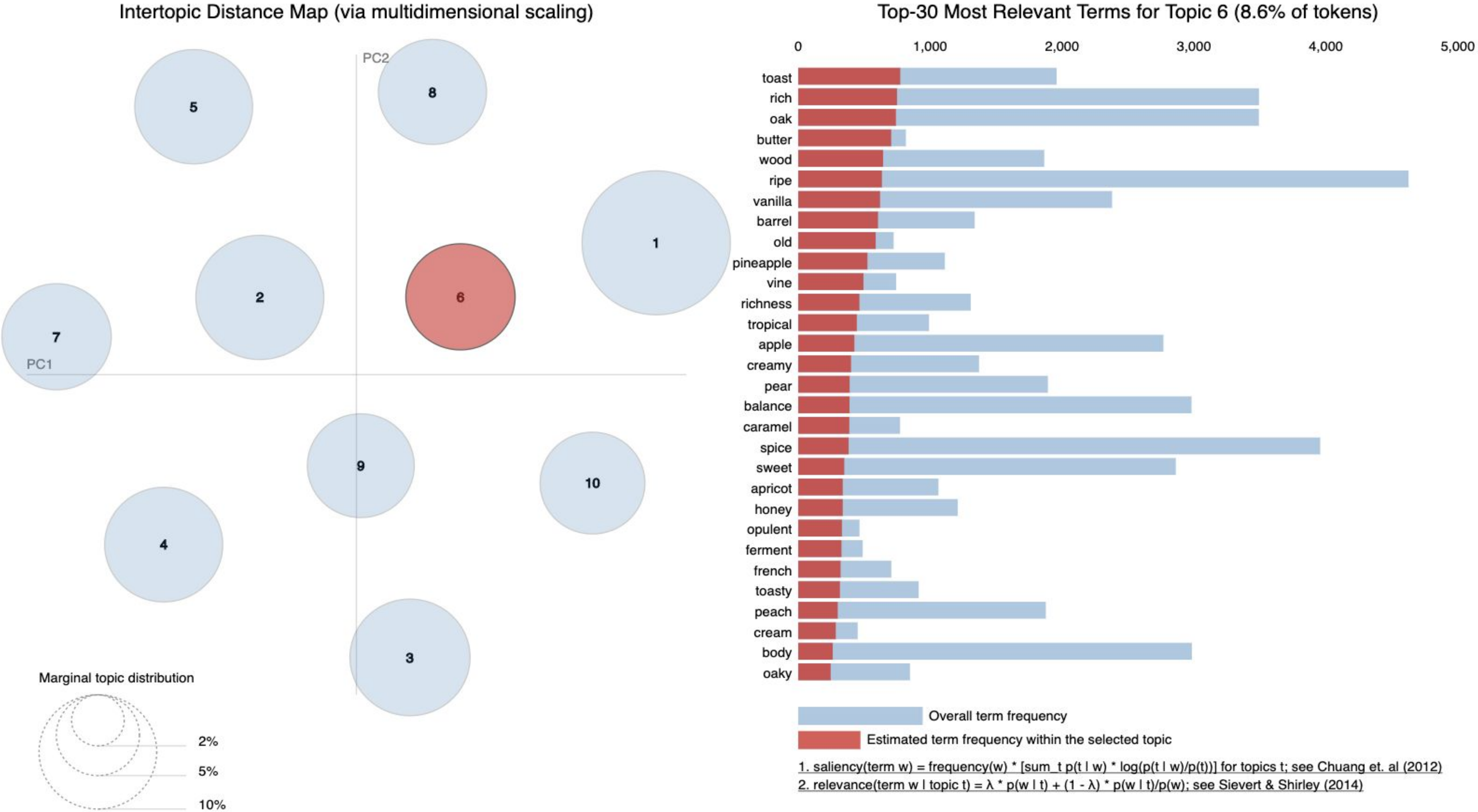

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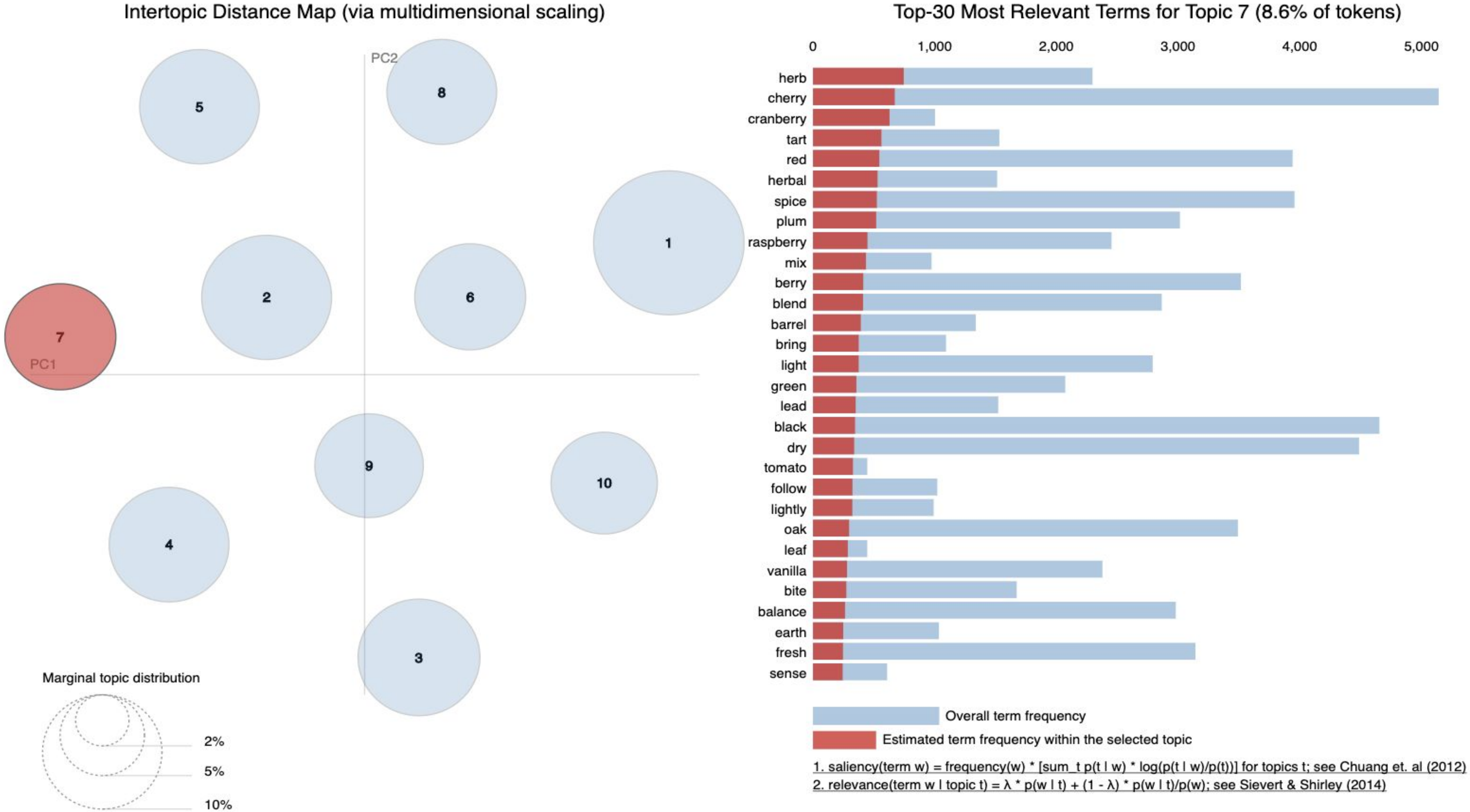

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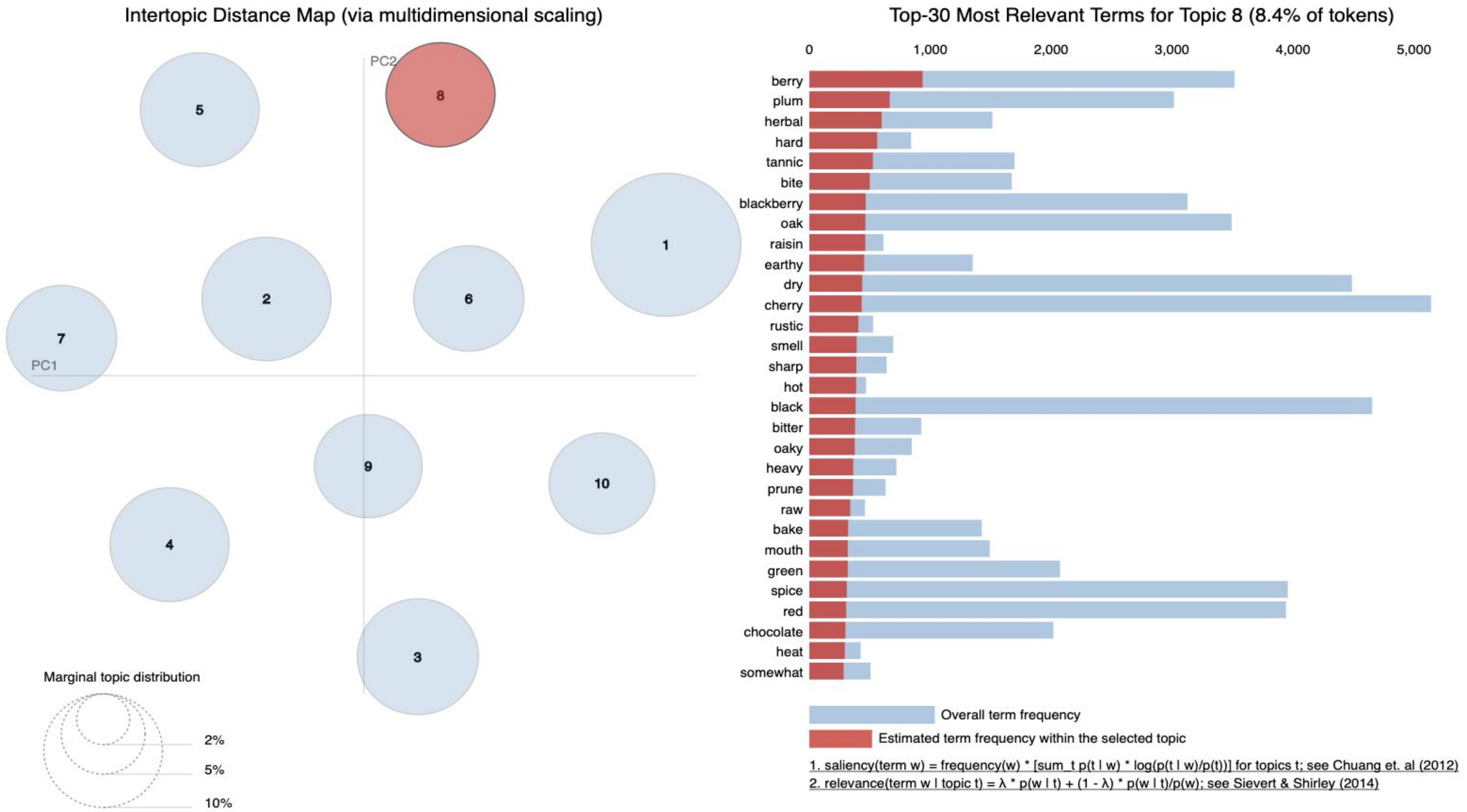

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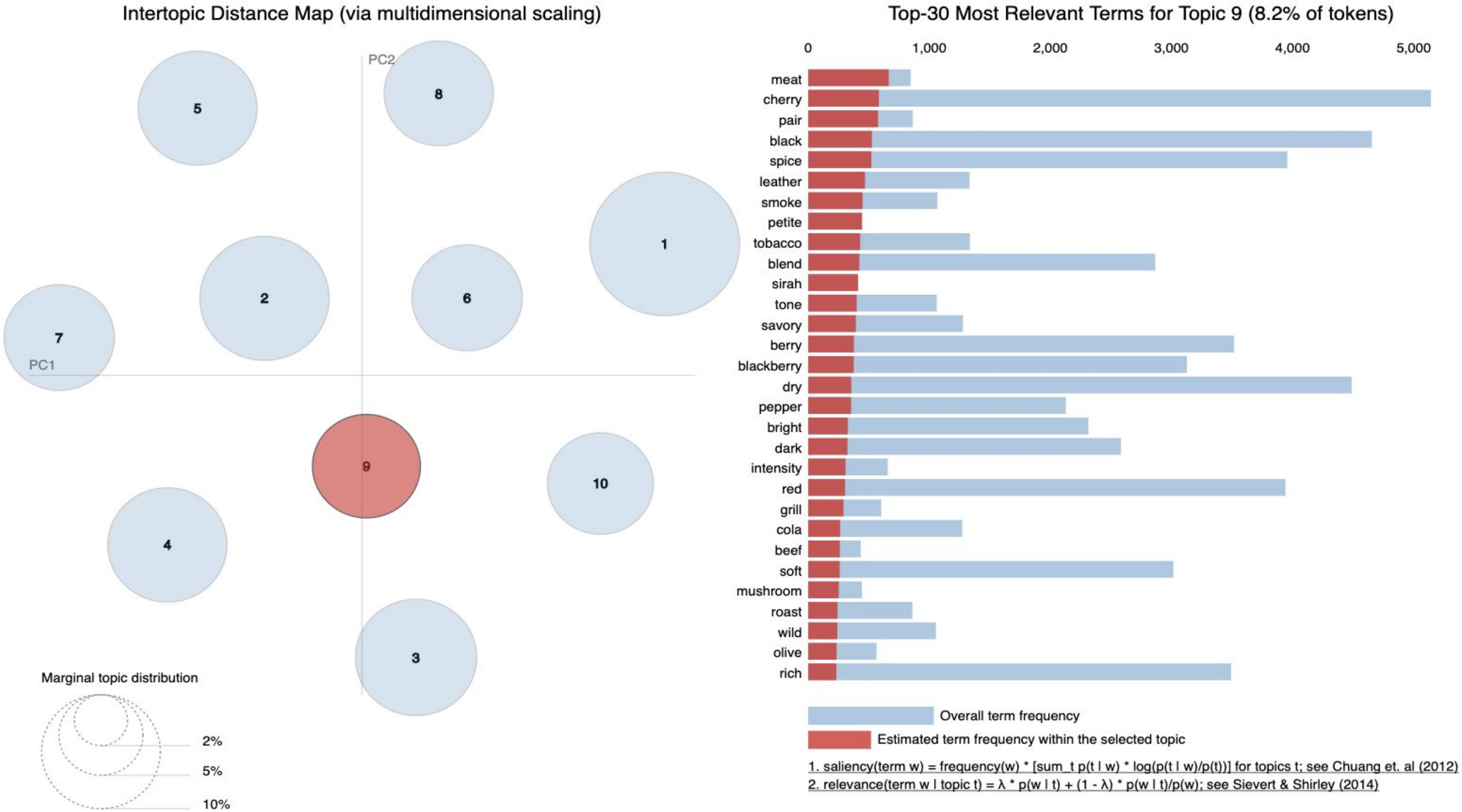

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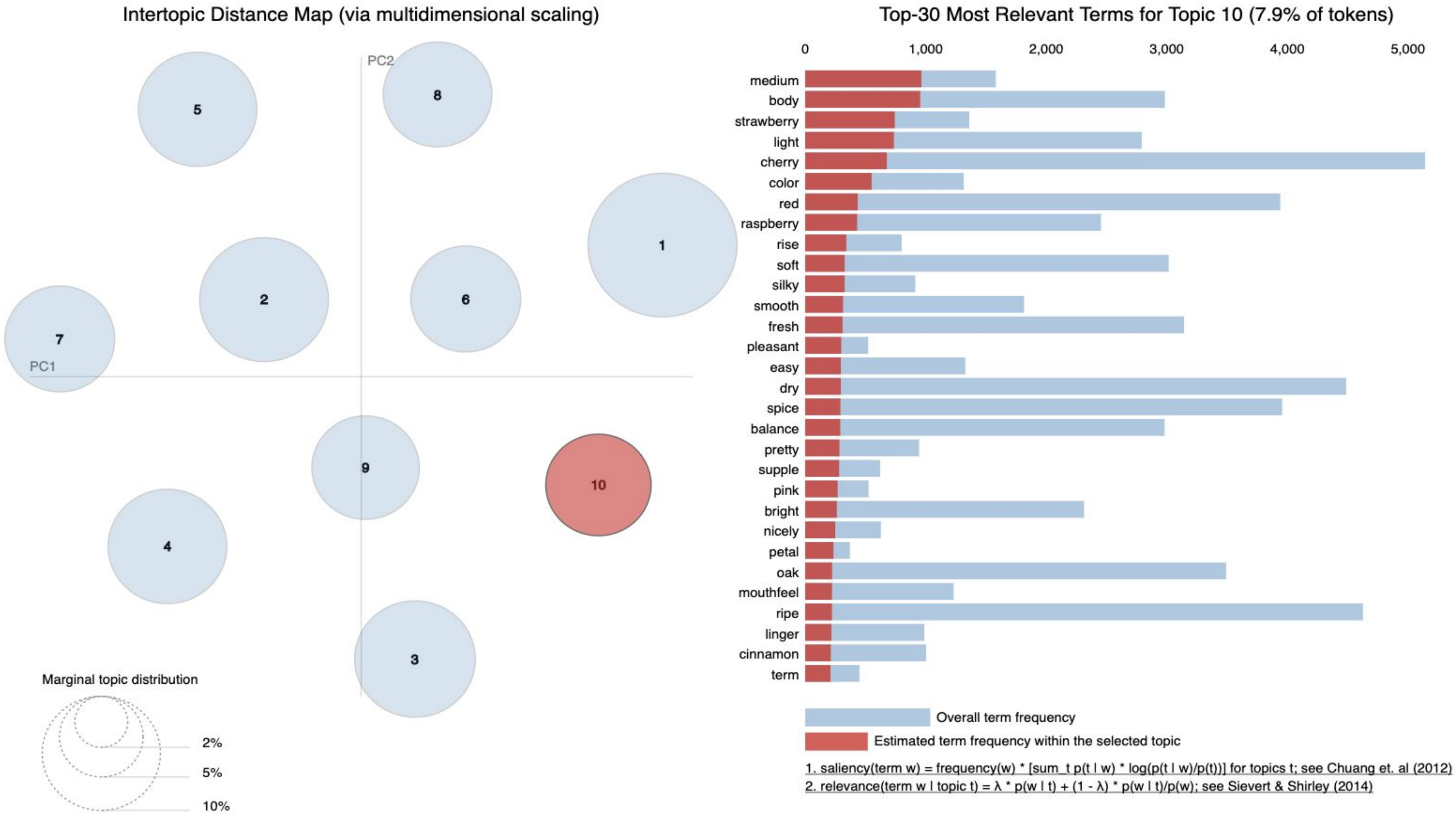

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CONCLUSIONS…

Sommeliers' jobs are safe! (For now…)

Basic clusters can't beat a good somm's taste-memory, but could help a casual wine drinker find more of what they like

FUTURE WORK

01 REFINE CLUSTERS

Go deeper into crucial vocabulary

02 RECOMMENDATION TOOL

Suggestions based on flavor groups

03 INSTASOMM

Make use of labelled data in dataset

THANK YOU!

QUESTIONS?

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