Integration of mProphet chromatogram peak identification probability model into Skyline

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Overview:

The Skyline Targeted Proteomics Environment has distinguished itself as a reliable and useful tool for chromatography-based quantitative proteomics. From its initial focus on selected reaction monitoring (SRM) to its current support for full-scan methods including MS1 filtering, targeted MS/MS and data independent acquisition (DIA – including the approach popularized as SWATH) measurements of peptide abundance have been based on areas under peaks in mass spectrometric chromatograms. Until now, however, peak identification within Skyline has relied on a limited set of features without the ability to derive a statistical confidence metric like a false discovery rate (FDR). To correct this shortcoming, we have integrated the mProphet scoring features, semi-supervised learning (SSL) algorithm and derivation of peak q values into Skyline..

Introduction:

Skyline now supports training an arbitrary number of chromatogram peak scoring models based on acquired data, using the mProphet SSL algorithm. These models consist of a set of coefficients, applied to available peak feature scores to derive an mProphet score, and a mean and standard deviation that define a normal distribution estimate of the null distribution for the mProphet scores. Different models may be trained for different experimental conditions. Once a model has been trained, it may be specified in Skyline and used for any number of experiments under the same conditions, without retraining under SSL. The null distribution parameters allow p value estimates, from which Skyline can estimate q values and FDR using the algorithm described by Storey, et al.

Figure 1: Peptide settings	Peptide Settings						
form showing a choice of trained mProphet scoring models as well as the legacy Skyline peak scoring model.	Digestion Prediction Filter Library Modifications Integration Peak scoring model: Peak scoring model: Skyline Legacy mProphet Gold Schubert SRM Course (Add> (Edit current> (Edit list>) OK Canc	el					

Methods:

In order to achieve this, we have implemented the following: Decoy peptide and transition generation

- Decoy peptide and transition import
- A calculator architecture allowing two calculator types
 - 1. Summary requiring only summary peak attributes
 - 2. Detailed requiring chromatogram points
- Calculating and storing detail scores during import
- Calculators for the original 8 mProphet scores ✓ Intensitv¹
 - ✓ Intensity correlation (dot-product)
 - ✓ Coelution²
 - ✓ Shape²
 - ✓ Reference correlation (dot-product)¹
- ✓ Retention time deviation¹
- ✓ Reference coelution²
- ✓ Reference shape²
- Calculators for several new scores ✓ Coelution count²
- ✓ Reference coelution count²
- Export mProphet features for testing with mProphet in R
- The mProphet SSL algorithm converted from R to C#
- Storey-Tibshirani q value calculation algorithm

In all cases, the resulting code was tested against data and results from original publications. Unit tests from OpenSWATH were used to validate some of the scores.

We have created two test Skyline documents:

- 1. The mProphet gold standard data set
- 2. A new document with decoy transitions generated in Skyline

Both have had SRM data imported and the new mProphet model editor used to train score coefficients for a composite linear scoring function.

	A	В	C	D	E	F		File	Edit	View	Se
1	Q1	Q3	transition id	tR	relative intensity	decoy		🖞 🖻	5	Undo	
2	669.91	629.40	yeast_p.AAAAGLAALVELIR.2.y5.1.light	41.8	70	FALSE		Targets	0	Redo	
3	669.91	742.48	yeast_p.AAAAGLAALVELIR.2.y6.1.light	41.8	59	FALSE			· .		
4	669.91	813.52	yeast_p.AAAAGLAALVELIR.2.y7.1.light	41.8	87	FALSE		- · · · · · · · · · · · · · · · · · · ·	×	Cut	
5	669.91	884.56	yeast_p.AAAAGLAALVELIR.2.y8.1.light	41.8	100	FALSE				-	
6	669.91	1054.66	yeast_p.AAAAGLAALVELIR.2.y10.1.light	41.8	71	FALSE				Сору	
7	674.91	639.41	yeast_p.AAAAGLAALVELIR.2.y5.1.heavy	41.8	70	FALSE		<u> </u>	PR.	Paste	
8	674.91	752.49	yeast_p.AAAAGLAALVELIR.2.y6.1.heavy	41.8	59	FALSE					
9	674.91	823.53	yeast_p.AAAAGLAALVELIR.2.y7.1.heavy	41.8	87	FALSE		<u> </u>	X	Delete	
10	674.91	894.57	yeast_p.AAAAGLAALVELIR.2.y8.1.heavy	41.8	100	FALSE		T		Select All	
11	674.91	1064.67	yeast_p.AAAAGLAALVELIR.2.y10.1.heavy	41.8	71	FALSE				Select All	
12	679.91	615.35	yeast p.RILEVLAALGAAAA.2.y8.1.light	41.8	70	TRUE				Find	
13	679.91	625.39	yeast p.RILEVLAALGAAAA.2.b13.2.light	41.8	59	TRUE				11110	
14	679.91	728.43	yeast p.RILEVLAALGAAAA.2.y9.1.light	41.8	87	TRUE				Find Next	
15	679.91	827.50	yeast p.RILEVLAALGAAAA.2.y10.1.light	41.8	100	TRUE					
16	679.91	1069.63	yeast p.RILEVLAALGAAAA.2.y12.1.light	41.8	71	TRUE		<u> </u>	1	Edit Note	
17	684.91	625.35	yeast p.RILEVLAALGAAAA.2.y8.1.heavy	41.8	70	TRUE					
18	684.91	625.39	yeast p.RILEVLAALGAAAA.2.b13.2.heavy	41.8	59	TRUE		<u> </u>		Insert	
19	684.91	738.44	yeast_p.RILEVLAALGAAAA.2.y9.1.heavy	41.8	87	TRUE				Pafina	
20	684.91	837.51	yeast p.RILEVLAALGAAAA.2.y10.1.heavy	41.8	100	TRUE				Kenne	
21	684.91	1079.63	yeast p.RILEVLAALGAAAA.2.y12.1.heavy	41.8	71	TRUE				Expand Al	
22	895.44	715.85	yeast p.AFDNALENSLNLQANR.2.b13.2.light	29.5	61	FALSE				Expand A	
23	895.44	828.47	yeast p.AFDNALENSLNLQANR.2.y7.1.light	29.5	82	FALSE				Collapse /	All
24	895.44	915.50	yeast p.AFDNALENSLNLQANR.2.y8.1.light	29.5	60	FALSE					
25	895.44	1029.54	yeast p.AFDNALENSLNLQANR.2.y9.1.light	29.5	80	FALSE		<u> </u>		Modify Pe	epti
26	895.44	1158.59	yeast p.AFDNALENSLNLQANR.2.y10.1.light	29.5	100	FALSE				Unique D	ti
27	900.45	715.85	yeast p.AFDNALENSLNLQANR.2.b13.2.heav	29.5	61	FALSE		- <u>-</u>		Unique Pe	-pu
28	900.45	838.48	yeast_p.AFDNALENSLNLQANR.2.y7.1.heavy	29.5	82	FALSE				Manage	
29	900.45	925.51	yeast_p.AFDNALENSLNLQANR.2.y8.1.heavy	29.5	60	FALSE				ivianage r	lesu
30	900.45	1039.55	yeast_p.AFDNALENSLNLQANR.2.y9.1.heavy	29.5	80	FALSE				709.32301	
31	900.45	1168.59	yeast_p.AFDNALENSLNLQANR.2.y10.1.heav	29.5	100	FALSE			≝" <u>∛</u>	/09.32/14	++ (r
32	905.44	719.87	yeast p.RNAQLNLSNELANDFA.2.b13.2.light	29.5	61	TRUE			Ψ_R.\	/IGVPAMF/	AAG
33	905.44	724.85	yeast_p.RNAQLNLSNELANDFA.2.y13.2.light	29.5	82	TRUE	-		<u>اللہ</u> 🕂	808.4349+	++
14 4	▶ ► transiti	ons / mProp	het peak groups / mProphet all peak gr			Þ	1		÷. A.	813 4390+	++ (ł

Figure 2a & b: Original mProphet gold standard transition list from supplementary information that was imported into Skyline (left) and decoy generation form used to create decoy transitions in new a document.

Results:







linear regression between measured retention times and iRT calculator scores and light and heavy precursor peak areas by run. The linear regression graph indicates that retention time prediction is unlikely to be a strong indicator of peak validity, since even with decoy peaks the R for the regression is 0.9986, probably because acquisition was scheduled in 4 minute windows around the predicted time.

Figure 6: Target-decoy histograms for the remaining 9 scores for the fully trained model shown in Figure 5, copied from the model training form.

http://proteome.gs.washington.edu/software/skyline

the null distribution may be an elusive goal.

References:

(1) Reiter L, Rinner O, et al. Nat. Methods. 2011/05; 8(5):430-5. (2) Malmstrom L, Malmstrom J, et al. J. Proteome Res. 2012/03; 11(3):1644-53.