

Identification of rare alternative splicing events in MS/MS data reveals a significant fraction of alternative translation initiation sites

Integration of transcriptome data is a crucial step for the identification of rare protein variants in mass-spectrometry (MS) data with important consequences for all branches of biotechnology research. Here, we used Splooce, a database of splicing variants recently developed by us, to search MS data derived from a variety of human tumor cell lines. More than 800 new protein variants were identified whose corresponding MS spectra were specific to protein entries from Splooce. Although the types of splicing variants (exon skipping, alternative splice sites and intron retention) were found at the same frequency as in the transcriptome, we observed a large variety of modifications at the protein level induced by alternative splicing events. Surprisingly, we found that 40% of all protein modifications induced by alternative splicing led to the use of alternative translation initiation sites. Other modifications include frameshifts in the open reading frame and inclusion or deletion of peptide sequences. To make the dataset generated here available to the community in a more effective form, the Splooce portal (<http://www.bioinformatics-brazil.org/splooce>) was modified to report the alternative splicing events supported by MS data.

- 15 **ASE** – Alternative splicing events
- 16 **TIS** – Translational initiation site
- 17 **FDR** – False discovery rate
- 18 **GTI-Seq** – Global translational initiation sequencing


19 **INTRODUCTION**

20 The development of large-scale technologies, including genomics, has revolutionized life

21 sciences. For example, the sequencing of the human genome in 2001 was a milestone in the
22 characterization of our genetic framework (Lander et al., 2001; Venter et al., 2001). The
23 advancement of sequencing technologies in the last few years has allowed the genome
24 sequencing of more than a thousand human individuals (1000 Genomes Project) (Consortium
25 2012). Likewise, the characterization of the transcriptome was also facilitated by these new
26 sequencing technologies. RNA-Seq techniques have allowed the identification of transcripts with
27 low copy numbers. Thus, the complete characterization of the transcriptome of different cell
28 types is already a reality today (Au et al., 2013; Peng et al., 2012; Xue et al., 2014). We know for
29 example about the large variability found in the transcriptomes of eukaryotes due to alternative
30 splicing and alternative polyadenylation. As a consequence of the emergence of these
31 technologies, an explosion of this type of data in public databanks and data repositories is already
32 occurring and exponential growth is expected for the next years. Improving bioinformatics
33 capabilities is crucial for the processing, storage and interpretation of results from large-scale
34 technologies.

35 While the technologies for sequencing of nucleic acids developed at an impressive speed,
36 the same did not happen with technologies for sequencing amino acids and proteins. Recently,
37 mass spectrometry-based proteomics achieved enough comprehensiveness and throughput to
38 allow in-depth characterization of “complete proteomes” (Beck et al., 2011; Nagaraj et al., 2011).
39 However, proteomic data acquisition is still restricted to few groups, even though public
40 availability of high depth proteomic data is increasing (Desiere et al., 2006; Vizcaino et al., 2013;
41 Vizcaino et al., 2014).

42 Alternative splicing is defined, basically, as a process in which identical pre-mRNA
43 molecules are processed in different ways in terms of usage of splice sites. This is a fundamental
44 process in all multi-cellular organisms being responsible for the creation of a large diversity of
45 proteins from a relatively small number of genes (Cork et al., 2012). Alternative splicing events

46 (ASE) have been extensively characterized using transcriptome data. On the other hand, only
47 recently proteome data have been used for global discovery of ASEs (Brosch et al., 2011;
48 Severing et al., 2011; Tress et al., 2008). The reason lies on the following: protein identification
49 by mass spectrometry is still routinely performed through the use of protein databases cataloged
50 and curated by public repositories such as nrNCBI and Uniprot. Most of these databanks contain
51 only a limited number of protein sequence isoforms, and single nucleotide polymorphisms and
52 ASEs are normally under-represented. This is generally so because peptide identification
53 approaches in proteomics mostly use probabilistic-based algorithms, and excessively large
54 databases would result in spurious spectral matches and, therefore, reduced number of positive
55 identifications (Wang et al., 2012). Thus, new approaches should be developed where ASEs can
56 be investigated without compromising database size and protein identification rates. Several
57 researchers have created strategies that use MS data repositories such as Peptide Atlas and in
58 silico protein database design using nucleotide sequence repositories or merging protein sequence
59 databases (Blakeley et al., 2010; Brosch et al., 2011). However, very few had applied RNA-Seq
60 data to offer isoform information at the transcriptome level, which then could be validated at the
61 protein level. For example, Sheynkman and colleagues (Sheynkman et al., 2013) developed a
62 strategy where RNA-Seq and MS data collected from the same samples had been applied for the
63 identification of splice junction peptides. However, applying such different expertise in any
64 project might not be a reality for a majority of laboratories  therefore, creating strategies that rely
65 on heavy bioinformatics analysis of nucleotide de novo sequence and validation through MS is
66 relevant.

67 Here, we investigated whether ASEs could be satisfactorily identified using size-limited
68 FASTA database, built from repositories of expressed sequences, which was then challenged by
69 MS data. Our group had recently developed Splooce, a database that integrates information from
70 transcriptome analysis, including RNA-Seq, to identify splicing variants (Kroll et al., 2012).

71 Protein entries created from Splooce were evaluated using MS/MS analysis, and a large number
72 of novel proteins isoforms were identified. Surprisingly we found that around 40% of all
73 modifications at the protein level were related to the use of alternative translation initiation sites
74 (TIS).

75 MATERIALS & METHODS

76 Protein variants identification using mass spectrometry and MaxQuant

77 Predicted proteins (in FASTA format) were collected from the full Splooce database and
78 filtered for entries showing alternative splicing events supported only by ESTs and/or RNASeq
79 expressed sequences. Those events were tagged as rare since they were not found in the set of
80 full-insert cDNA sequences (RefSeq, mRNA), which usually have well characterized coding
81 sequences. Any pattern of combined alternative splicing event was allowed. As default parameter,
82 Splooce only reports events that are supported by at least two expressed sequences. For the
83 prediction of protein sequences, Splooce uses a simple ab-initio strategy. Briefly, human entries
84 from the Reference Sequence database (Pruitt et al., 2014) were modified by introducing
85 alternative splicing patterns observed from the transcriptome data. Thus, full-length alternative
86 cDNA sequences were created from expressed sequence fragments that often cover only a small
87 fraction of coding sequences. As a final step, prior to the translation process, new open reading
88 frames are predicted based on their length. Our final set of predicted proteins, containing 120,299
89 entries, can be downloaded from <http://www.bioinformatics-brazil.org/~jkroll/sploocemm>.
90 Human entries from Uniprot (from December 2013) (Magrane & Consortium 2011) were added
91 to the Splooce dataset to facilitate the visualization of identified peptides that are not unique to
92 the Splooce set. The final dataset contained 209,927 entries.

93 We submitted the collection of entries from Splooce plus Uniprot to a dataset of MS/MS
94 peptide information collected from 11 tumor cell lines that were publicly available at the Tranche

95 Network (currently discontinued). The whole collection of MS data was derived from the
96 laboratory of Dr. Mathias Mann (Geiger et al., 2012). Four RAW files from this dataset were not
97 used because they were apparently corrupted in the depository. We submitted the remaining files
98 to a MaxQuant (version 1.4.1.2) (Cox & Mann 2008) search using the following parameters:
99 initial search with a precursor mass tolerance of 20 ppm that were used for mass recalibration;
100 main search precursor mass and fragment mass were searched with mass tolerance of 6 ppm. The
101 search included variable modifications such as Met oxidation, N-terminal acetylation (protein),
102 and Pyro-Glu (Q)(E). Carbamidomethyl cysteine was added as a fixed modification. Minimal
103 peptide length was set to 7 amino acids and a maximum of two miscleavages were allowed. The
104 false discovery rate (FDR) was set to 0.01 for peptide and protein identifications. In the case of
105 identified peptides that are shared between two proteins, these are combined and reported as one
106 protein group. Protein table output was filtered to eliminate the identifications from the reverse
107 database, and common contaminants.


108 **Protein variants identification using a *de novo* strategy**

109 We also decided to test the ability to identify peptides characterizing ASEs using a *de*
110 *novo* approach rather than a probabilistic one using a database. MS raw files were submitted to
111 *de novo* sequence identification using the PEAKS software (Ma et al., 2003). Parameters were set
112 as: i) trypsin with no proline restriction as enzyme, ii) two miscleavages allowed and iii)
113 precursor ion and fragment ion error of 10 ppm. Furthermore, carbamidomethyl (Cys) as fixed
114 modification, while protein N-term acetylation, Met oxidation and pyro-Glu (Q / E) were also
115 allowed as variable modifications. Only peptide sequences with more than 80% average coverage
116 certainty were selected for further analysis. Coverage certainty is calculated on an amino acid per
117 amino acid basis, i.e., only in cases where the software was able to precisely detect mass of the
118 amino acid removed from two neighboring daughter ions.

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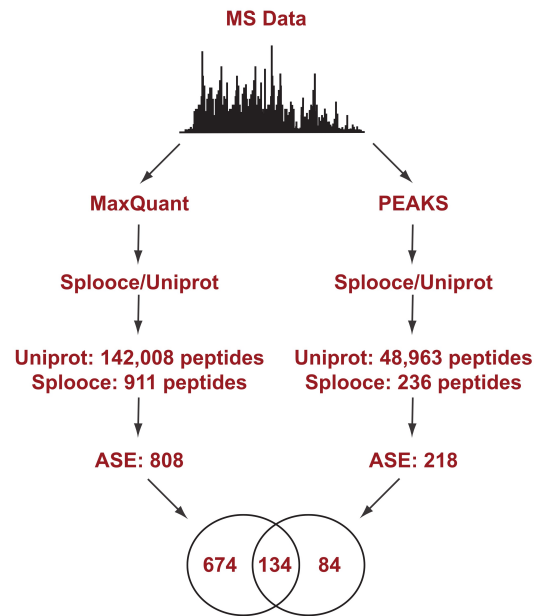
120 Identification of peptides supporting alternative splicing events

121 The output file of identified peptides obtained from MaxQuant and PEAKS were filtered
122 for peptides observed specifically on Splooce entries. As described above, all MaxQuant peptides
123 showing reversed and contaminant tags were removed from the data set. The resulting peptides
124 were then compared against an unmodified set of RefSeq sequences, which Splooce uses as
125 template for predicting new proteins. Any peptide observed for a Splooce entry, but not observed
126 for its respective unmodified RefSeq, was classified as an ASE supporting peptide since it aligns
127 uniquely to the alternative protein sequence. Additionally, any ASE supporting peptides matching
128 the beginning of proteins were classified as alternative translation start sites.


129 A clear limitation in a “database-based” approach is a reduction in peptide/protein
130 identification due to an increase in the search space by creating an excessively large database.
131 Therefore we restricted our database to a size approximately twice as big as Uniprot. Protein
132 identification using our database obtained approximately 500 proteins less than the original
133 publication, a variation of less than 5%. Since the original publication used a version of the
134 discontinued International Protein Index database, we also submitted the dataset to Uniprot
135 database without our in house Splooce sequences (data not shown), since Uniprot and IPI would
136 have closer number of entries and therefore, similar search space. The Uniprot result identified
137 approximately 200 proteins less than the original publication. Such differences are probably due
138 to: i) different identified unique entries in Uniprot or IPI, ii) small differences in the parameters
139 between our MaxQuant search and the original publication, and/or iii) differences in MaxQuant
140 performance since we used an updated version compared to the one used the original publication.
141  egardless, we concluded that even doubling the database size with Splooce entries, protein
142 identification penalty was irrelevant for the approach efficiency.

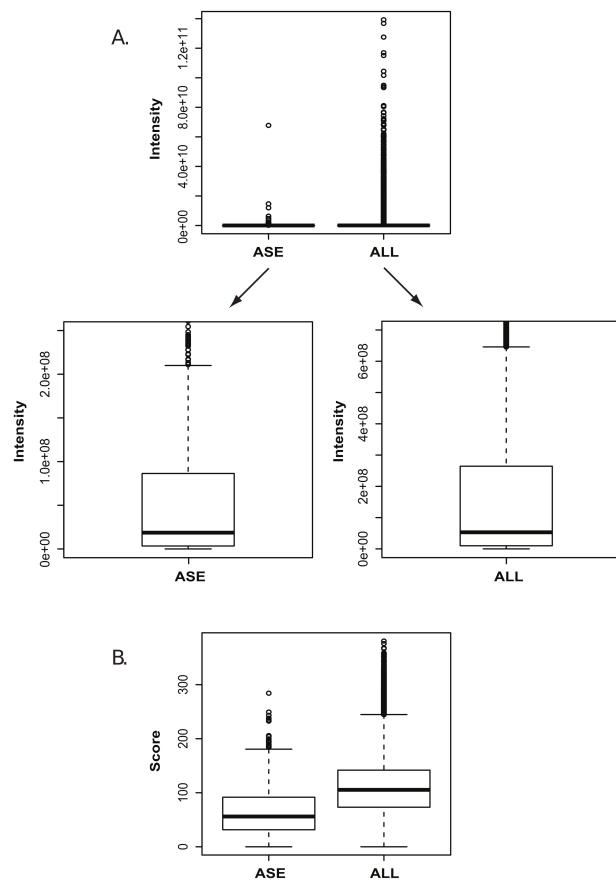
143 **RESULTS AND DISCUSSION**144 **Identification of splicing variants in the MS/MS data**

145 Splooce was used as a source to create a database of predicted protein isoforms in FASTA
146 format, which was then searched against MS/MS spectra. A data set of 120,299 non-redundant
147 protein sequences was created based on rare ASEs that were not observed for full-insert cDNA
148 sequences (see Experimental Procedures for more details). That data set was merged to 89,602
149 Uniprot entries from the December 2013 release. A public collection of MS RAW files was then
150 selected for protein identification. Only files from a publication that reported good level of
151 instrument sensitivity and proteomic depth (Geiger et al., 2012) were used and such MS dataset
152 was challenged against the Splooce-derived protein sequences using two peptide identification
153 approaches, one based in probabilistic method and another one based on *de novo* sequencing
154 (Figure 1). Both methods offer unique advantages and limitations. *De novo* sequencing provides
155 unbiased peptide identification, not limited to its theoretical existence in a database. On the other
156 hand, sequence information can only be obtained from good to high quality MS/MS data, and
157 partial sequence information is generally discarded. Algorithms using a protein database overall
158 offer a higher identification rate, since partial sequence information, together with accurate mass
159 measurement of the precursor peptide ion, can still provide positive identification. *De novo* data
160 also offer additional possibilities since once a given sequence information is obtained it can be
161 aligned against sequence repositories to provide protein identification.



162 **Figure 1.** Experimental design flowchart. Briefly, public MS data from 11 cell lines (Geiger et
 163 al., 2012) were submitted to peptide identification using a Splooce database either by a
 164 probabilistic approach (MaxQuant) or a *de novo* approach (PEAKS). Identified peptides were
 165 sorted and those characterizing alternative splicing events not present in Uniprot were compared.

166 Initial analysis using the probabilistic approach (MaxQuant) allowed us to identify a total
 167  42,926 unique peptides representing 11,237 protein groups. Supplementary files S1 reports
 168 the MaxQuant peptide output containing the identification features for both the total peptides
 169 identified and the ones identified only in the Splooce database. As expected, the vast majority
 170 (142,008) of these peptides are already present in Uniprot. However, 911 peptides, representing
 171 808 ASE, were only observed for Splooce entries.



172 **Figure 2.** Peptide signal intensity (A) and scoring (B) distribution for all peptides (ALL) and
 173 sorted alternative splicing events (ASE) in the probabilistic approach. ASE peptides were on
 174 average an order of magnitude less abundant than the whole peptide population, consequently
 175 with lower average scoring.

176 We next plotted individual peptide intensities and scores from both the complete peptide
 177 dataset and peptides uniquely identified in Splooce. Data overview of the complete dataset
 178 showed, as previously reported, an intensity SDam of 7 orders of magnitude. The peptides
 179 characterizing the rare ASEs were observed mostly at the bottom half of the intensity
 180 distributions, with an average distribution approximately one order of magnitude lower than the
 181 complete Uniprot set (Figure 2A). While the score distribution seemed similar, ASE-derived
 182 peptides, on average, had a lower distribution (Figure 2B), which could be a consequence of

183 poorer MS/MS from lower intensity ions.

184 In addition, the same RAW files were submitted to PEAKS, a software capable
185 of determining a MS/MS sequence without the support of a database. Since no FDR can be
186 estimated without the support of reversed sequences artificially created from a database, this
187 analysis was restricted to spectra where fragment ion mass sequence could be measure with an
188 average confidence of at least 80%. Using this approach, approximately 50,000 peptides were
189 identified in Uniprot and Splooce (data not shown), and from those only 236 peptides, confirming
190 218 splicing events, could be identified in the same Splooce-derived database as used in the
191 probabilistic approach. From those, 134 ASE were already observed in the probabilistic
192 approach. By merging the results of the two strategies, we characterized a total of 892 ASE
193 (Supplementary File S2 and S3).

194 As expected, the *de novo* method identified a smaller proportion of proteins and peptides
195 than the probabilistic method when submitted to a BLAST-like alignment versus the same
196 Splooce database. In fact, a smaller number of splicing events were detected in the *de novo*
197 method when compared to the probabilistic one. An explanation for this could be that since most
198 ASE events characterized by the probabilistic method are seen in the bottom part of signal
199 intensity, they most probably generated partial MS/MS information that did not fulfilled the
200 criteria required by us for reporting good quality *de novo* sequences. With this observation we
201 therefore conclude that performing a probabilistic method using an in house database generates
202 more information than *de novo* sequencing.

203 The frequency of each type of alternative splicing was next calculated for all events
204 identified in our strategy. Simple events like exon skipping, alternative splice borders and intron
205 retention showed proportional frequencies when compared to general Splooce statistics (Table 1).
206 Moreover, no ASEs resulting from dual-specificity splice sites were identified, since these events
207 are very uncommon and usually found within UTR sequences (Zhang et al., 2007). Splooce is

208 also a database that focus on the analysis of combined ASEs (CASEs), and it was previously
 209 shown that approximately half of all alternative expressed sequences may have more than one
 210 ASE along their sequences (Kroll et al., 2012). The analysis presented here confirms the same
 211 finding at the proteome level. The most frequent combined event was the skipping of several
 212 adjacent exons (up to 11 exons), followed by adjacent alternative splice sites.

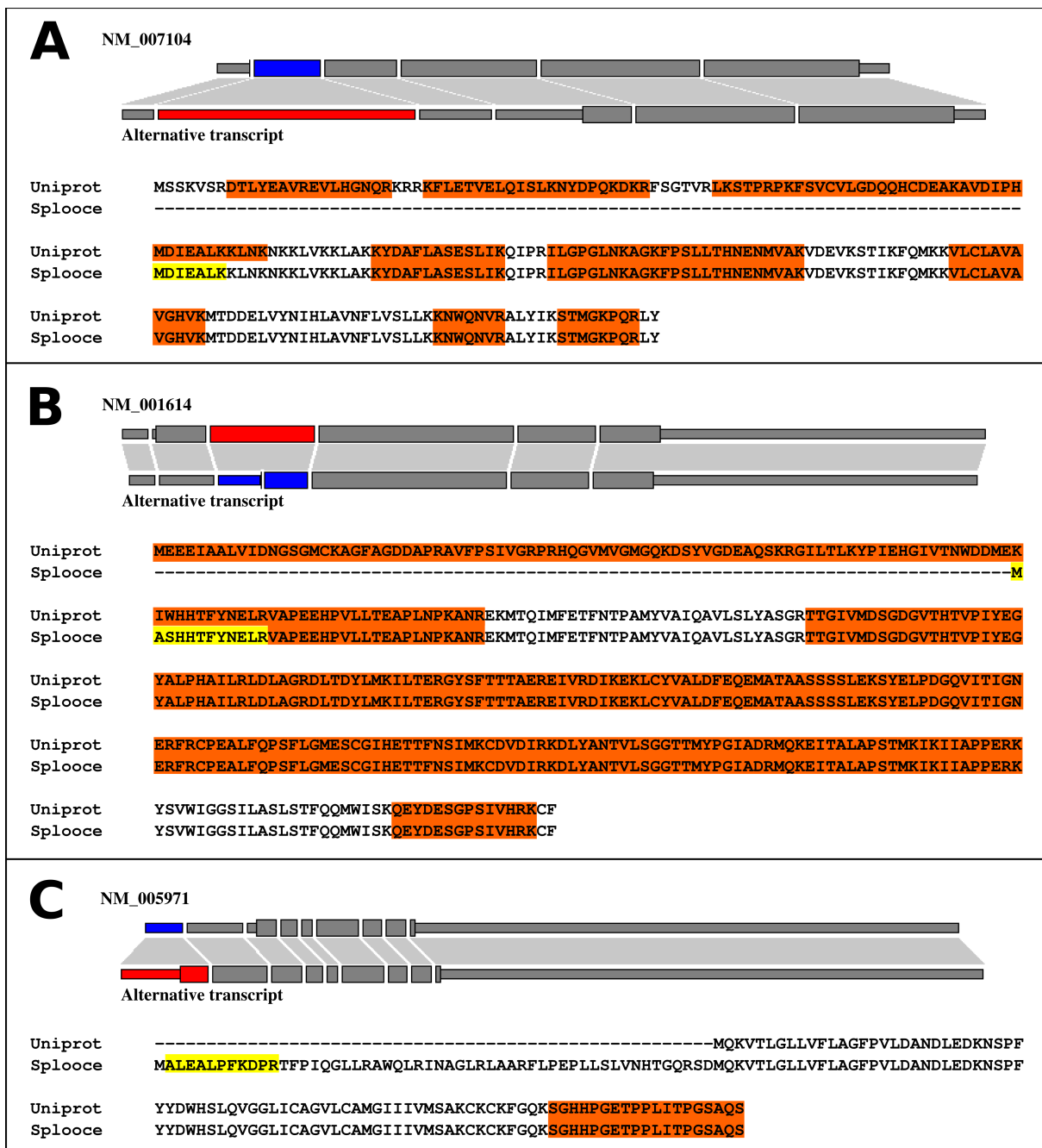
Alternative Splicing Event	Total Events from Splooce	Events identified by the MS/MS analysis
Exon skipping	38060 (35%)	182 (39%)
Alternative 3' splice site	30172 (29%)	130 (28%)
Alternative 5' splice site	27585 (25%)	90 (20%)
Intron retention	12632 (11%)	61 (13%)
Dual-specific splice site	112 (0%)	0 (0%)

213 **Table 1** Amount of alternative splicing events identified by the MS/MS analysis compared to the
 214 total number of events available from the Splooce database.

215 **Alternative TIS represents the majority of events at the proteome level**

216 We further explored what types of events were observed in the identified peptides.
 217 Interestingly, 355 ASEs, out of the 892 (40%), showed a pattern consistent with the use of an
 218 alternative TIS due to an ASE (Figure3, Supplementary File S2). The remaining 537 proteins
 219 showed different types of variations along their protein sequences (Supplementary file S3). Files
 220 S2 and S3 not only contain a resumed version of the results described in this section, but also
 221 report protein sequence alignments for Uniprot and Splooce sequences of all proteins identified
 222 with a rare ASE. Peptides shared between both databases, in addition to the Splooce-specific
 223 peptide(s), are highlighted in the alignment. Most importantly, each alignment contains a link to
 224 the Splooce website where information and statistics for that rare ASE can be collected.

225 The high proportion of alternative TIS was further explored. All new protein isoforms
226 showing an alternative TIS were searched against the TISdb database (Wan & Qian 2014), a
227 collection of TIS obtained from a genome-wide method (GTI-Seq) developed by the same
228 authors (Lee et al., 2012). We found that only one TIS present in our list was present in the TISdb
229 providing therefore a proteome validation for that respective TISdb entry. Several reasons could
230 explain the small overlap between the two datasets such as: i) the different nature of the samples
231 used in both studies, ii) the fact that most of the TIS present in TISdb are non-canonical and start
232 with others codons than ATG (we restricted our analysis to ATG-associated TIS) and iii) the lack
233 of proteome validation in most of the studies that populated TISdb.





234 **Figure 3.** Alignments between normal (Uniprot/RefSeq) and alternative (Splooce) proteins,
 235 showing different categories of alternative TIS observed for our data. Sequences highlighted in
 236 orange represent MS peptides found for the Uniprot/RefSeq proteins, and sequences highlighted
 237 in yellow represent peptides found exclusively in the alternative sequences from Splooce.
 238 Peptides that align specifically to a sequence from Splooce are supposed to characterize ASEs. A:
 239 Alternative TIS is downstream the original one; B: Same as A, although the beginning of the

240 protein sequence is directly affected by the ASE. C: Alternative TIS is upstream the original one.

241 Wilson and colleagues have suggested that the association between ASE and TIS are restricted to
242 the amino-terminus of proteins where both events are used to produce isoforms that differ at their
243 amino end. Almost 2,000 events like that were identified at the transcriptome level but few (17
244 instances) were confirmed in a limited search against MS/MS data (Wilson et al., 2014). We
245 wondered whether this type of event would be frequent in our dataset of 355 TIS. Visual
246 inspection of all 355 cases identified only 29 instances (8%) that would fit the model from
247 Wilson et al., (2013) (for more details, see Supplementary file S2). The low level of validation of
248 such cases at the proteome level, also seen by the authors in their original report, raises doubts
249 about their widespread occurrence. All remaining 326 cases of TIS in our dataset were analyzed
250 to identify the effect of the ASE in the protein sequence originally present in the reference
251 sequence. In only three cases, the alternative TIS was upstream of the original ATG codon. In all
252 remaining cases, the ASE occurred upstream of the alternative TIS and disrupted the respective
253 ORF. An alternative ATG codon, always located downstream of the ASE, is then used as a new
254 TIS. Interestingly, only in 15% of these cases (48 out of 323) the ATG codon used in the TIS is
255 the first one downstream of the ASE.

256 CONCLUSIONS

257 A limitation on  facing in this type of analysis the definition of a proper false discovery
258 rate when adding entries in a database *ad infinitum*. Any observed MS/MS information in such
259 approaches will be tagged to the “best-fit” theoretical peptide present in the database, regardless
260 if that is the correct one. Even though identification engines such as Mascot and MaxQuant have
261 proof-check algorithms to quantify FDR rate, incorrect MS/MS information  might still be
262 reported as true. Therefore there will be always the risk that peptides that are present in the

263 sample but not represented in the database are incorrectly assigned. In addition, there will be a
264 size limit where adding more protein entries created by RNAseq information will be detrimental
265 to the analysis, rather than beneficial. For a good isoform discovery phase study to reliably work,
266 a compromise between database size and validation rounds using complementary databases must
267 be created. A desirable strategy would be to create a collection of public, high quality datasets
268 such as the one used in this work and use them for database-based splicing discovery using
269 different versions of the Splooce database. Recently, similar approaches have been successfully
270 implemented for mapping expressed genes, pseudogenes and characterization of new open
271 reading frames (Kim et al., 2014; Wilhelm et al., 2014), but little was shown regarding splicing
272 isoforms. Therefore, such approach using Splooce databases with public MS data for ASE
273 discovery is feasible and promising for further characterization of the human proteome draft.

274 In summary, a new strategy for the identification of splicing variants in MS/MS data is
275 provided here allowing us to confirm at the proteome level more than 800 new variants. We
276 extended previous observations linking ASE and TIS and provided validation for hundreds of
277 new TIS events. We have upgraded the Splooce portal to take into account the integration of
278 MS/MS data in the validation of splicing variants.

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