Sequence Analysis

14-3-3-Pred: Improved methods to predict 14-3-3-binding phosphopeptides

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ABSTRACT

Motivation: The 14-3-3 family of phosphoprotein-binding proteins regulate many cellular processes by docking onto pairs of phosphorylated Ser and Thr residues in a constellation of intracellular targets. Therefore, there is a pressing need to develop new prediction methods that use an updated set of 14-3-3-binding motifs for the identification of new 14-3-3 targets, and to prioritize the downstream functional determinants for the X residues (Yaffe et al., 1997; Yaffe, 2002; Zhu et al., 2005). The 14-3-3s also have strong preferences with respect to the sequences immediately flanking the phosphorylated residues (Yaffe et al., 1997; Yaffe, 2002; Zhu et al., 2005).

Results: Here, a comprehensive set of 14-3-3-binding targets from the literature was used to develop 14-3-3-binding phosphosite predictors. Position-specific scoring matrix (PSSM), support vector machines (SVM), and artificial neural network (ANN) classification methods were trained to discriminate experimentally-determined 14-3-3-binding motifs from non-binding phosphopeptides. ANN, PSSM and SVM methods showed best performance for a motif window spanning from -6 to +4 around the binding phosphosite, achieving Matthews correlation coefficient of up to 0.60. Blind prediction showed that all three methods outperform two popular 14-3-3-binding site predictors, Scansite and ELM. The new methods were used for prediction of 14-3-3-binding phosphosites in the human proteome. Experimental analysis of high-scoring predictions in the FAM122A and FAM122B proteins confirms the predictions and suggests the new 14-3-3-predictors will be generally useful.

Availability: A standalone prediction webserver is available at http://www.compbio.dundee.ac.uk/1433pred. Human candidate 14-3-3-binding phosphosites were integrated in ANIA: Annotation and Integrated Analysis of the 14-3-3 interactome database.

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Supplementary information: Supplementary data are available at Bioinformatics online.

1 INTRODUCTION

The 14-3-3 phosphoprotein-binding proteins interact with many intracellular targets. Changes in the engagement of 14-3-3s with different sets of target phosphoproteins cause coordinated shifts in cellular behavior in response to growth factors and other stimuli (Mackintosh, 2004; Bridges and Moorhead, 2005; Johnson et al., 2010, 2011). 14-3-3s are boat-shaped dimers that dock onto specific pairs of phosphorylated Ser and Thr residues (Obsil and Obsilova, 2011). The phosphosite pairs are often located in tandem on the same target protein, and are typically >15 amino acid residues apart to allow engagement with both docking sites in the central groove of the 14-3-3 dimer (Yaffe et al., 1997; Yaffe, 2002; Zhu et al., 2005). The 14-3-3s also have strong preferences with respect to the sequences immediately flanking the phosphorylated residues (Yaffe et al., 1997; Yaffe, 2002; Zhu et al., 2005).

Early analyses of known 14-3-3-binding sites indicated R(S)X1,2(pS)X(P) as a 14-3-3-binding motif (Muslin et al., 1996; Mackintosh, 2004). Later screening of libraries for phosphopeptides that displayed optimal binding to 14-3-3s, identified two consensus 14-3-3-binding motifs, namely Mode I (RX(pS/T)XP) and Mode II (RX(F/Y)X(pS)XP), with subtle preferences and negative determinants for the X residues (Yaffe et al., 1997; Yaffe, 2002; Obsilová et al., 2008). These sequence motifs served as the basis for a position-specific scoring matrix (PSSM) to predict potential 14-3-3-binding phosphosites in Scansite (Obenauer, 2003). A more recent survey showed that most experimentally determined 14-3-3-binding sites (dubbed gold-standards) conform to mode I motifs, having at least one basic residue in the positions -3 to -5, relative to the phosphorylated Ser/Thr, and never a +1 proline. However, the proline at +2 is found in fewer than 50% of cases, and often the serine in the -2 position relative to the 14-3-3-binding phosphosite is a residue that is annotated as phosphorylated (Johnson et al., 2010). Additionally, Mode III sites, in which the phosphorylated residue is the penultimate residue in the C-terminal tail of a protein target, have also been reported (Coblitz et al., 2006; Panni et al., 2011).

Recently, a further striking pattern was identified in the human 14-3-3 interactome. The majority of well-defined human 14-3-3-binding phosphoproteins were discovered to be 2R-ohnologues (Tinti et al., 2012). This means that they belong to protein families of two to four members that were generated by the two rounds of whole-genome duplication (2R-WGD), which marked the evolutionary origins of the vertebrate animals ~500 million years ago (Makino and McLysaght, 2010; Hummiecki and Heldin, 2010). Most of the new genes were negatively selected and lost. However, those that were retained in families of two to four members are highly enriched in signalling proteins that bind to 14-3-3s (Tinti et al., 2012; Hummiecki and Heldin, 2010). In case studies, protein...
families were identified whose members share one 14-3-3 binding site in common (termed the ‘lynchpin’). Lynchpins also align with a serine or threonine residue in the pro-orthologue proteins from the pre-2R-WGD invertebrate chordates, *Branchiostoma* (amphioxus, lancelet) and *Ciona* (tunicates, sea squirts). In contrast, the second sites may differ on different family members, and may be phosphorylated by different protein kinases. These findings led to the proposal that 14-3-3 diners may have played a mechanistic role in the regulatory divergence of 2R-onnologue families: The lynchpin hypothesis proposes that conservation of one ‘lynchpin’ 14-3-3-binding site gave the freedom for the second site to change, and perhaps become a consensus site for phosphorylation by a different protein kinase (Johnson et al., 2011). The resulting protein families therefore operate as ‘signal multiplexing’ systems that are regulated by a wider array of protein kinases than would be possible if the function were performed by only a single protein.

Currently, the Scansite 14-3-3 predictor (Obenauer, 2003) is the most commonly used software tool to identify potential 14-3-3-binding phosphosites. Scansite was trained on peptide-libraries derived from a limited number of experimentally-defined 14-3-3-binding sites, but these training datasets no longer accommodate the diversity of known 14-3-3-binding phosphopeptides. Another source of information on 14-3-3-binding sites is the ‘eukaryotic linear motif’ database ELM (Puntervoll, 2003). ELM uses regular expressions and context-based filtering to derive pattern probabilities based on a few dozen Mode I, Mode II and non-consensus motifs.

There are now >2000 phosphoproteins that have been found to display affinity for 14-3-3 in high-throughput (HTP) proteomics experiments (Pozuelo Rubio et al., 2004; Jin et al., 2004; Nishioka et al., 2012). Accordingly, there is a need to extend predictors to include 14-3-3 binding sites that do not conform to Mode I binding and to test the signal multiplexing hypothesis. A more comprehensive picture of potential 14-3-3 binding sites would help to define how the complete 14-3-3-interactome system works. The ANIA (ANnotation and Integrated Analysis of the 14-3-3 interactome) web-service and database (Tinti et al., 2014) integrates multiple datasets on 14-3-3-binding phosphoproteins and provides an up-to-date gold-standard dataset of experimentally determined 14-3-3-binding phosphosites of all known Modes. In this paper, three new classifiers of 14-3-3-binding sites are described that have been experimentally defined. Although the likely NEG sites are located in 14-3-3-binding proteins, these sites are thought unlikely to bind 14-3-3s since there is currently no evidence of proteins that bind 14-3-3 through multiple pairs of phosphosites. The resulting POS and NEG datasets comprised balanced numbers of phosphopeptides that were further processed for training of the classifiers.

To explore motif patterns that are in agreement with the modes of binding previously proposed, five non-symmetrical motif windows around the phosphoSer/Thr sites were defined, including: [-3:1], [-4:2], [-5:3], [-6:4], and [-7:5]. These motif windows ranged from 4 to 12 residues in width not including the central phosphoSer/Thr residue. The peptides in the POS and NEG datasets were also filtered for sequence redundancy at a range of identity thresholds for all pairwise peptide comparisons. When working with small peptides, a single amino acid difference can be critical for determining specificity. Thus, determining redundancy in short peptides is not straightforward. In this paper, redundancy is defined by differences of 1...k/2 amino acids, where k is length of the peptide. Thus, redundancy thresholds ranged from a minimum of one residue difference up to half of the size of the motif window (equivalent to 50% redundancy level). For example: for motif window [-6:4] that comprises 10 residues, five levels of redundancy were investigated with a minimum number of differences ranging from one to five. Since the number of redundancy thresholds investigated depends on the size of the motif window in analysis, all combinations of windows and redundancy thresholds were tested in model training and testing.

In order to reduce the risk of bias, the resulting pairs of balanced POS and NEG datasets from different combinations of motif windows and redundancy thresholds were further split into two independent training and testing subsets. This gave 240 (75%) and 78 (25%) peptides for training and testing respectively. After selecting the best overall models in training and testing, final methods were trained using the full non-redundant training and testing subsets, comprising 318 POS and 318 NEG peptide examples in total (100%) (Supplementary Table S1 and S2). An additional independent and ‘blind’ test dataset (BLIND) comprising 38 experimentally-defined 14-3-3-binding sites was collected from the literature (Supplementary Table S3). Following the same strategy used for preparing the training datasets, 32 likely non-binding phosphosites were selected as BLIND negatives (Supplementary Table S4).

### 2 METHODS

#### 2.1 Data collection and preprocessing

The human proteome was retrieved from the UniProt database (June 2013 release) and all Ser/Thr residues located in every protein sequence. A collection of annotated phosphoSer/Thr sites (phosphoproteome) was gathered from PhosphoSitePlus (October 2013 release) (Hornbeck et al., 2004).

A list of 300 experimentally determined 14-3-3-binding phosphosites was collected from ANIA (Tinti et al., 2014) and further extended from the literature to give 322 gold-standard 14-3-3-binding sites (POS) (Supplementary Table S1). A negative dataset (NEG) (Supplementary Table S2) was assembled from the literature cited in Johnson et al. (Johnson et al., 2010), resulting in 93 phosphosites. To prepare balanced sets of POS and NEG examples, 230 additional likely non-binding sites were randomly selected from a subset of proteins for which two 14-3-3-binding sites had been experimentally defined. Although the likely NEG sites are located in 14-3-3-binding proteins, these sites are thought unlikely to bind 14-3-3s since there is currently no evidence of proteins that bind 14-3-3 through multiple pairs of phosphosites. The resulting POS and NEG datasets comprised balanced numbers of phosphopeptides that were further processed for training of the classifiers.

#### 2.2 Classification methods

##### 2.2.1. Artificial neural network (ANN)

ANN models were trained using the R package RSNNs (Bergmeir and Benítez, 2012) and the Stuttgart Neural Network Simulator (SNNS; http://www.ra.cs.uni-tuebingen.de/SNNS). For ANN training, each of the 20 different amino acids was encoded as a binary vector of length 20. For example: Ala was encoded as [1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0], whereas Arg was encoded as [0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0]. This pattern was followed for all 20 amino acids while gaps or other ambiguous amino acids were encoded as [0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0]. Accordingly, phosphopeptides of length k (4 ≤ k ≤ 12) were encoded by vectors of length 20k. The final ANN model had 20 input nodes, a single hidden layer with 20 nodes, and one output layer with one output node. Training was performed by the backpropagation algorithm with momentum term (“Backpropomomentum”), learning parameter η = 0.2, and momentum term μ = 0.05.

##### 2.2.2. Position-specific scoring matrix (PSSM)

PSSMs were implemented in Python (http://www.python.org) and assembled by adapting the procedure described by Ferrari and colleagues (Ferrari et al., 2011). Amino acid frequency matrices were derived from POS and
NEG datasets and from a background (BGD) dataset, made up of all peptides that have annotated phosphoSer/Thr sites (phosphoproteome). For each motif window of length \( k \) of the alignment (4 \( \leq k \leq 12 \)); a PSSM was assembled with 20 rows (20 amino acids plus gaps or ambiguous (X)), \( AA = \{ A, R, N, D, C, Q, E, G, H, I, L, K, M, F, P, S, T, W, Y, V, X \} \) and \( k \) columns, where the values represent the frequency of amino acid \( i \) \( \in AA \) at the \( j^{th} \) position \( j = 1 \ldots k \) in the multiple alignment of all peptides. Equation 1 defines the final score \( S(p) \) assigned to each queried phosphopeptide \( p \) which is calculated by adding up the scores for all the positions, where

\[
S(p) = \sum_{j} \frac{POS_{i,j} - NEG_{i,j}}{BGD_{i,j}}
\]

\( POS_{i,j}, NEG_{i,j}, \) and \( BGD_{i,j} \) are the frequency values for amino acid \( i \) at position \( j \), in the POS, NEG and BGD matrices, respectively.

2.2.3 Support vector machines (SVM)

SVM models were trained and parameterized using the Python module PyML (http://pyml.sourceforge.net), which contains a set of non-linear kernels specifically developed for training and classification of biological sequences (Ben-Hur et al., 2008). The final SVM model employed the weighed-degree kernel (Sonnenburg et al., 2005), with soft margin constant \( C \), which specifies the degree of separation between the two training classes of support vectors in the hyperplane, was set to one. Lastly, the cosine kernel was applied to normalize the kernel values.

2.3 Feature selection for the ANN models

Two independent alphabet reduction systems were tried. Both methods grouped the 20 amino acids in 10 classes according their physicochemical properties, and were encoded as an orthogonal 10-length binary (Li et al., 2003; Livingstone and Barton, 1993).

Further features were also explored as inputs to the ANN model. Protein secondary structure predictions and solvent accessibility were computed by Ipred (Cole et al., 2008), which provides predictions of \( \alpha \)-helix, \( \beta \)-strand, random coil, and solvent accessible or buried. In addition to the 20-length binary vector of amino acid encodings, every residue position including the central Ser/Thr was encoded as a 5-length binary vector or alternatively encoded as a vector of raw Ipred prediction scores \( \{0:0:1:0\} \), resulting in a vector of length 20k + 5k + 1). Similarly, three methods for predicting natively unstructured/disordered regions in proteins (Dosztányi et al., 2005; Linding, 2003; Linding et al., 2003) were computed using the JABAWS package (Troshin et al., 2011). Peptide motifs were classified as disordered or structured by four methods, and were encoded as a binary vector of length 2, which resulted in an encoding vector of length 20k + 2(4). IUPred prediction scores \( \geq 0.5 \) were used to define disordered regions, whereas for GlobPlot, the Dydx algorithm with a threshold of \( \geq 0.0 \) was used. Regions predicted by both DisEMBL algorithms: HOTLOOPS and REM465; were considered for disorder classification.

2.4 Evaluation methods

The performance of each classifier was evaluated by Jackknife (leave-one-out cross-validation) on the training and testing data, before a final test on the BLIND dataset. The performance of each method was assessed by receiver operating characteristic (ROC) curves which were plotted at various thresholds (Fawcett, 2004). The area under the ROC curve (AUC) (Sonego et al., 2008) was used as the primary performance measure. Additional standard metrics were calculated for each method including: sensitivity (SN, equivalent to recall) (Eq. 1), specificity (SP) (Eq. 2), positive predictive value (PPV, equivalent to precision) (Eq. 3), accuracy (ACC) (Eq. 4), and Matthews correlation coefficient (MCC) (Eq. 5), where TP, FP, TN, FN denote the number of true positives, false positives, true negatives and false negatives, respectively.

\[
SN = \frac{TP}{TP + FN}
\]

\[
SP = \frac{TN}{TN + FP}
\]

\[
PPV = \frac{TP}{TP + FP}
\]

\[
ACC = \frac{TP + TN}{TP + TN + FP + FN}
\]

\[
MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}
\]

Evaluation and statistical analysis was performed in the R statistical language (http://www.r-project.org) and ROCR package (Sing et al., 2005). Sample correlation analysis was performed by the Pearson correlation coefficient (r). For two-sample paired tests, the Wilcoxon-Mann-Whitney test and the Student’s t-test were performed. The null hypothesis was inferred at a 95% level of confidence.

2.5 Biochemical methods

The cDNA encoding human FAM122A (Q96E09) was amplified from IMAGE consortium EST clone 6182641 (coding for NM_138333.3 CDS) and FAM122B (Q7Z09) was from IMAGE consortium EST clone 3841054 (coding for NM_145284.3 CDS). Three isoforms of FAM122C (Q6P4D5) were cloned: NP_620174.1 amplified from IMAGE clone 4699951 (152 residues); Q6P4D5.1, amplified from IMAGE clone 5229041 (195 residues); and AAH65225.1, amplified from IMAGE clone 5724414 (96 residues). cDNAs were cloned as BamHI/NotI inserts into the multiple cloning site of pCDNA5 FRT/TO that adds a C-terminal GFP tag to the expressed protein. Mutants were made using PCR mutagenesis and DNA sequencing was performed by The Sequencing Service, University of Dundee (www.dnaseq.co.uk). Plasmids are available from the MRC-PPU reagents website (mrccpureagents.dundee.ac.uk).

Proteins were isolated using GFP-Trap® (ChromoTek) from lysates of transfected human embryonic kidney 293 (HEK293) cells, using a lysis buffer that preserves their in vivo phosphorylation status. The isolated proteins were tested for retention of co-purified endogenous 14-3-3 proteins (K19 pan-14-3-3 antibody, Santa Cruz Biotech), and for their ability to bind directly to 14-3-3s in Far-Western overlays, as in X(ANIA). Where indicated, isolated proteins were dephosphorylated, or not, as in X(ANIA) prior to analysis of their interaction with 14-3-3.

3 RESULTS AND DISCUSSION

3.1 Development and evaluation of 14-3-3 classifiers

Three new 14-3-3 classifiers were developed in this work. Data preprocessing was performed so that all combinations of motif window length and redundancy thresholds were evaluated in model training and model testing. The comparison of the area under the ROC curve (AUC) scores by Jackknife for the resulting classifiers showed that the highest performance was achieved at a redundancy threshold of at least one residue difference (sequence identity <90%), for a motif region spanning from -6 to 4. A motif window [-6:4] agrees with observed 14-3-3-binding modes (Johnson et al., 2010) and performed better in this study than [-7:7] which has been previously selected for this kind of classification task (Obenauer, 2003; Miller et al., 2008).
As shown in Fig. 1A, all three methods performed similarly well in model training and model testing, with AUC scores ranging from 0.84 (for the SVM in model training) to 0.87 (for PSSM and SVM in model testing). Fig. 1B shows the performance of the final models trained using balanced and non-redundant POS and NEG datasets (318 POS and 318 NEG peptide examples), generated by combining non-redundant training and testing sub-sets. ANN and PSSM showed an AUC of 0.86, whereas the SVM showed an AUC of 0.85. Although globally the performance of the final methods is not significantly different, the ANN presented the highest Matthews correlation coefficient (MCC) score of 0.59±0.01 (SD), accuracy (ACC) of 79.6±0.6% and a positive predictive value (PPV) of 79.8±1.6%.

Since phosphorylated Ser/Thr usually lie at the protein surfaces enabling kinase/phosphatase activity, as well as regulation by the 14-3-3s (Vandermarliere and Martens, 2013), additional features such as secondary structure, solvent accessibility, and protein disorder, were tested to see their effect on performance, as was feature-selection by amino acid alphabet reduction. Although these approaches have proved useful in a number of classification tasks (for example (McDowall et al., 2009; Aytuna et al., 2005)), here they added complexity, but did not give a significant improvement in the performance of the methods developed here (data not shown).

3.2 Comparison with other predictors

The performance of the new classification methods developed here was compared with Scansite (Obenauer, 2003) and ELM (Puntervoll, 2003), using an additional dataset (the BLIND set) that was not used for training the methods. The BLIND dataset comprises 38 experimentally-defined 14-3-3-binding phosphopeptides and 32 non-14-3-3-binding sites. Raw Scansite prediction scores were obtained by querying Netphorest (Miller et al., 2008), that fully implements the original Scansite PSSM. Categorical classification scores were also obtained for each BLIND phosphoprotein, from the Scansite2 (Obenauer, 2003), Scansite3 (unpublished work by Tobias Ehrenberger, 2012), and ELM webservers (Dinkel et al., 2013). Scansite2 provides prediction scores based on 14-3-3 Mode I motifs that fall into three stringency levels: high, medium, and low. Scansite3, a Java implementation of Scansite2, enables search for a fourth stringency level: minimum. ELM uses context-based filtering and text-mining to improve the accuracy of assigned pattern-matching probabilities based on Mode I and Mode II 14-3-3-binding as well as non-consensus 14-3-3-binding. Overall, any phoshoSer/Thr site for which a prediction score was provided (at a particular stringency level, in the case of Scansite), was considered to be classified as 14-3-3-binding. All the remaining sites were classified as non-14-3-3-binding. Although other methods exist to predict 14-3-3-binding sites (Chan et al., 2011; Panni et al., 2011) no software or pre-computed predictions were available for comparison to the methods developed here.

As shown in Table 1, all three methods developed here showed higher MCC scores (up to 0.60 for ANN and PSSM), when compared Netphorest Scansite, Scansite2 and Scansite3 at different stringency levels, and ELM (up to 0.52 for Scansite2 low and ELM). Indeed, the new methods present the best accuracy (ACC of 80.0% for the ANN and 78.6% for PSSM and SVM), compared to
accuracies of the other predictors, which are generally lower than 75.7% (obtained for Scansite2 low). The performance scores of the new methods agree well with the performance observed in model training and testing (Fig. 1). However, the PPV observed for the BLIND dataset is higher (from 79.8% for the final models compared to ≥85.3% PPV for the BLIND dataset), which might be an outcome of the unbalanced composition of the BLIND dataset. A consensus predictor achieved 0.61 MCC and 80.0% ACC by averaging the scores from the three methods. Both Scansite2 and Scansite3 high stringency showed 100% PPV and 100% specificity (SP). This results from the fact that both methods incorrectly classify most sites as non-14-3-3 binding and give small numbers of TP and FP (zero FP in this particular case) but high FN. In terms of sensitivity (SN), the best method was Scansite3 minimum with 84.2% SN, compared to the ANN that showed 76.3% SN. Here, Scansite3 minimum correctly predicted 32 out of 38 POS examples, whereas the ANN correctly predicted 29/38. Although Scansite predictors show higher SN and SP, the new predictors show a better balance between these two metrics, which leads to superior ACC and MCC scores.

Two-sample sequence analysis of the final POS and NEG datasets revealed that Mode I is indeed the most common, accounting for ~46% enrichment of Arg at position -3, ~31% enrichment of Pro at +2 position. Additionally, poorer enrichment of Ser and Leu at positions -2 and +1, respectively, as well as depletion of Pro at +1, is also observed. A similar profile is observed for the BLIND dataset which might explain why Scansite low and minimum correctly classifies POS examples equally well as the consensus predictor. However, non-consensus binding motifs are better covered by the methods introduced here since the consensus motifs I and II represent less than 30% of POS in both training and blind datasets. The correlation between the consensus predictor and NetPhorest Scansite scores, for prediction of 14-3-3-binding phosphopeptides in the human proteome (section 3.3), is only $r = 0.65$ ($p < 0.001$), indicating that a fair number of peptides produce discordant predictions by Scansite and the methods developed here.

Overall, based on the performance measures and benchmark results shown in Table 1 and Fig. 1C, all methods introduced in this study outperform the previous predictors with Scansite2 low and ELM the closest rivals. The Consensus predictor is significantly better than all the Scansite predictors and ELM, based on the MCC scores obtained for the BLIND dataset ($p<0.05$). Since the exact peptide datasets used for training Scansite are not known, it is likely that the real performance of Scansite will be lower, as some of the tested examples could have been used for its training. Similarly, ELM adds literature annotation for known 14-3-3-binding phosphosites when available, so its prediction performance is perhaps over-optimistic. In fact, ~60% (15/24) TP were annotated from the literature, making this benchmark evaluation moderately biased in favour of ELM. Intriguingly, Scansite2 and Scansite3 presented some classification differences at high and low stringency levels. Whether this difference is the result of the new implementation of Scansite3, potentially setting new underlying stringency thresholds, or due to the addition of a minimum stringency level is not clear.

### 3.3 Prediction and experimental testing of 14-3-3-binding phosphosites in the human proteome

All 1,543,965 Ser/Thr residues in the 20,245 proteins of the human proteome as released in June 2013, were considered as potential 14-3-3 sites and ranked according to the methods developed here. The consensus classifier predicted a total of 75,891 potential binding sites in 17,214 proteins. This corresponds to 4.9% of all Ser/Thr sites with an average of 4 sites per protein. Considering only the set of 117,640 proteins for which phos-
Table 2. Top 20 high scoring predictions and their respective scores. Proteins that have shown affinity to 14-3-3 in high-throughput (HTP) experiments and 2R-ohnologue members were identified by querying ANIA. FAM122A and FAM122B were experimentally verified to bind 14-3-3 in this study.

<table>
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<th>Rank</th>
<th>Protein</th>
<th>Description</th>
<th>Site</th>
<th>Motif</th>
<th>Consensus</th>
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<td>PPP1R3G</td>
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<td>CRARSRFSLPAD</td>
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<td>RCRSKTPFAC</td>
<td>1.66</td>
</tr>
<tr>
<td>16</td>
<td>TBC1D22A c</td>
<td>TBC1 domain family member 22A</td>
<td>167</td>
<td>PLLRQSLPHS</td>
<td>1.65</td>
</tr>
<tr>
<td>17</td>
<td>HUWE1 b</td>
<td>E3 ubiquitin-protein ligase HUWE1</td>
<td>649</td>
<td>MRRRRSEPLG</td>
<td>1.65</td>
</tr>
<tr>
<td>18</td>
<td>UBR4 b</td>
<td>E3 ubiquitin-protein ligase UBR4</td>
<td>2715</td>
<td>NKRHKTLPSS</td>
<td>1.62</td>
</tr>
<tr>
<td>19</td>
<td>CEP170 b</td>
<td>Centrosomal protein of 170 kDa</td>
<td>644</td>
<td>GERRRTLQPL</td>
<td>1.60</td>
</tr>
<tr>
<td>20</td>
<td>TMEM40</td>
<td>Transmembrane protein 40</td>
<td>137</td>
<td>GLRRRSGESPAS</td>
<td>1.59</td>
</tr>
</tbody>
</table>

The consensus predictor averages the scores obtained by the three methods: ANN, PSSM and SVM.

Proteins that have shown affinity to 14-3-3 in HTP experiments;

Protein members of 2R-ohnologue families;

phoSer/Thr sites have already been annotated, the number of predicted sites falls to 10,881 in 5,483 proteins. This corresponds to 9.2% of all Ser/Thr sites in the phosphoproteome and an average 2 candidate phosphosites per protein, which reduces the potential number of PP, since proteins known to be phosphorylated potentially bind to 14-3-3 dimers. This approach makes it more amenable for prioritizing experimental investigation. As shown below, two high-ranking ANN predictions were further tested by experiment.

Table 2 shows the top 20 high-scoring candidates predicted by the three methods on the phosphoproteome. Predicted proteins include: Sperm-specific antigen 2 (3b); Sorbin and SH3 domain-containing protein 1 (5b); Negative elongation factor E (6b); E3 ubiquitin-protein ligase HUWE1 (17b); E3 ubiquitin-protein ligase UBR4 (18b); and Centrosomal protein of 170 kDa (19b); all of which had been previously detected in 14-3-3-binding capture experiments (Tinti et al., 2014; Wang et al., 2011), but whose 14-3-3-binding sites remained elusive. High-scoring predictions by the consensus predictor support that these proteins partner with 14-3-3s, however further experiments have to be performed to validate these candidate binding-sites.

Two of the predicted sites, ranked at 2nd and 11th with consensus scores of 1.88 and 1.67, are for Family with sequence similarity 122A and 122B (FAM122A and FAM122B). FAM122 is a family of three uncharacterized proteins (A, B and C). FAM122A and FAM122B is a pair of 2R-ohnologues, while FAM122C evolved by tandem duplication of FAM122B in mammals (adjacent genes at Xq26.3). Such tandem duplication of 2R-ohnologues is rare (Makino and McLysaght, 2010).

Consistent with the 14-3-3-Pred results (Table 2), all three FAM122 family members displayed phosphorylation-dependent binding to 14-3-3 proteins when isolated from transfected cells (Fig. 2A). The binding of 14-3-3 to FAM122A was abolished by its dephosphorylation (Fig. 2B) and by substitution of Ser37 of FAM122A with alanine (Fig. 2C). Although phosphoSer62 and phosphoThr64 of FAM122A also had relatively high 14-3-3-Pred scores (0.614 and 1.076 respectively), mutation of these residues did not affect 14-3-3 binding to FAM122A isolated from cells cultured in standard serum-containing medium (Fig. 2C). However, in the absence of Ser37, stimulating cells with the adenylate cyclase activator forskolin caused a marked increase in 14-3-3 binding to FAM122A, which was abolished when Ser62 was also mutated to alanine and when cells were pre-treated with H89, which is a non-specific cAMP-dependent protein kinase (PKA) inhibitor (Fig. 2D). These data indicate that a 14-3-3 dimer binds to both phosphoSer37 and phosphoSer62 on FAM122A, the latter likely phosphorylated by PKA. Similar experiments showed that 14-3-3 binds to phosphoSer25 and forskolin-regulated phosphoSer50 of FAM122B, and to phosphoSer29 (ILRRVNSAPLI)
Thus, this is an example of a 2R-ohnologue family for which protein members share a conserved 14-3-3-binding ‘lynchpin’. In fact, half of the top 20 candidate proteins (10/20) belong to 2R-ohnologue families. The benchmark results for the BLIND dataset, as well as prediction of 14-3-3-binding sites in the human proteome and the analysis of top high-scoring predictions, suggests the new classifiers developed in this study will be generally useful for identifying potential 14-3-3 sites. Although the methods developed here were not specifically developed to predict pairs of 14-3-3-binding sites due to the limited set of proteins for which two binding sites are known, the example of the FAM122 2R-ohnologue family illustrates its use to investigate both primary and secondary 14-3-3-binding phosphosites.

A standalone web-server providing a simple yet useful interface to the new methods to score potential Ser/Thr centered motifs for likelihood of binding 14-3-3 proteins is freely available at http://www.compbio.dundee.ac.uk/1433pred. The predictions described here were also integrated in the ANIA database. ANIA adds a functional layer to the peptide-based predictions, by looking for pairs of sites >15 residues apart and by the analysis of sequence alignments of 2R-ohnologue families to identify potential lynchpins (Tinti et al., 2012, 2014). In addition to the human proteome, predictions on proteomes of model organisms, such as Arabidopsis thaliana, where several 14-3-3-binding targets have been identified (Ferl, 1996; de Boer et al., 2013), will be performed and added to ANIA in the future.

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**Conflict of Interest:** none declared.

**REFERENCES**


