Data and text mining

# PPaxe: easy extraction of protein occurrence and interactions from the scientific literature 

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#### Abstract

Motivation: Protein-protein interactions (PPIs) are very important to build models for understanding many biological processes. Although several databases hold many of these interactions, exploring them, selecting those relevant for a given subject, and contextualizing them can be a difficult task for researchers. Extracting PPIs directly from the scientific literature can be very helpful for providing such context, as the sentences describing these interactions may give insights to researchers in helpful ways. Results: We have developed PPaxe, a python module and a web application that allows users to extract PPis and protein occurrence from a given set of PubMed and PubMedCentral articles; It presents the results of the analysis in different ways to help researchers export, filter and analyze the results easily. Availability: PPaxe web demo is freely available at https://compgen.bio.ub.edu/PPaxe. All the software can be downloaded from https://compgen.bio.ub.edu/PPaxe/download, including a command-line version and docker containers for an easy installation. Contact: jabril@ub.edu Supplementary information: Supplementary data are available at Bioinformatics online.


## 1 Introduction

Protein-protein interactions (PPIs) play a major role in many biological processes, such as cancer, regeneration, and the development of many diseases (Ian et al., 2012); which makes the identification of these interactions a key point for the understanding of these processes. Databases such as iHOP (Hoffmann et al., 2005) have helped researchers to navigate the scientific literature using genes and proteins as drivers. Further tools exist in order to automatically retrieve interactions described in the scientific literature (Raja et al., 2013; Quan et al., 2014; Zhao et al., 2016); however, the accessibility to these tools for researchers is rather difficult, either because they can't be easily downloaded or because they lack a user-interface. Here we present PPaxe, a python module and a web application, superseding already developed code used for a previous analysis of the protein network of retinitis pigmentosa; that code was referred to as Sparser in the methods section of Boloc et al. 2015.

## Implementation

PPaxe reads a text file with a list of PubMed identifiers and downloads all the necessary articles. PPaxe downloads either abstracts from Medline or full-text articles from PubMed Central, depending on the option provided by the user. On the web application, the user can also provide a wellformatted PubMed query, so that the tool can retrieve the list of publication identifiers directly from NCBI PubMed; or a plain-text file with the text to be analyzed.

PPaxe uses Stanford CoreNLP (Manning et al., 2014) for name entity recognition (NER) of proteins and genes. Three datasets were used in order to train the The Stanford Named Entity Recognizer: AImed (Bunescu et al., 2005), MedTag (Smith et al., 2005) and BioInfer (Pyysalo et al., 2007). First, each sentence was tokenized by Stanford CoreNLP; then, a Conditional Random Field (CRF) classifier was trained. Performance of the NER tagger was assessed by 2-fold crossvalidation. Once the NER is trained, PPaxe extracts all the co-occurring proteins in each sentence and for each pair of them, computes several features, as described on Suppl. Mat. Table S1, which will be used in order to identify pairs as interacting


Fig. 1. PPaxe web interface and output examples. a) Web application input form; b) Graph visualization from the HTML report. c) Sentences containing PPIs retrieved from the analysis of four PubMed abstracts (PMIDs: 15640847, 20729546, 25196150, and 25211495), presented in the HTML output as a searchable table. The Confidence value (shown in the table and on the graph edges) corresponds to the normalized percentage of votes of the predictor (ranging from 0 to 1). Enlarged version available as Suppl. Mat. Figure S1.
or not. The prediction is based on a Random Forest Classifier from scikit-learn (Pedregosa et al., 2011), trained over the annotated sentences of AImed, LLL-challenge (Nédellec, 2005) and BioInfer. A votes cut-off of 0.55 was selected to detect interacting proteins from sentences, based on the performance of the classifier on our evaluation (estimated using 10-fold cross-validation).

Finally, PPaxe produces several possible outputs: an HTML page with all the PPIs, the sentences in which they were found, a table with all the proteins found in the specified articles, a graph visualization made with the JavaScript library cytoscape.js (Franz et al., 2015), and a PDF with a summary of the analyses. PPaxe is also distributed as two docker images, a command-line application and a web application, respectively; which can be retrieved from the downloads page. The web application docker image runs a localhost server on a customizable port. PPaxe python modules are available too.

## Results and Discussion

Protein and gene name tagging by the Stanford CoreNLP was evaluated by 2 -fold cross-validation on the datasets of AImed, MedTag and Bioinfer; which resulted in a precision of $74.5 \%$, a recall of $70.0 \%$, and an F1 of $72.1 \%$. As PPaxe does not use any dictionary table in order to identify the proteins, it is able to tag protein symbols of any species, or even newly described proteins and genes. However, it cross-checks the identifiers against the aliases provided by the HUGO Gene Nomenclature Committee as a prior normalization step (Yates et al., 2017).

PPaxe is able to retrieve protein-protein and genetic interactions without needing to define specific patterns or rules, which makes the application's use broader and more general than other previously mentioned approaches, such as PPInterFinder (Raja et al., 2013). PPaxe considers only a narrow selection of features, namely POS composition, token distance, and keywords (see Suppl. Mat. Table S3), freeing PPaxe of syntactical parsing and the posterior processing of dependency trees. On an Intel Core i7 machine, PPaxe took $\sim 2^{\prime \prime}$ to download and analyze 10 articles, $16^{\prime \prime}$ for $100,2^{\prime} 36^{\prime \prime}$ for 1,000 , and $28^{\prime} 54^{\prime \prime}$ for 10,000 . An assessment of the interaction extraction performance and a validation over BioGRID (Stark et al., 2006) are described in Suppl. Mat. evaluation section
and is shown on Table S1 and Table S2. PPaxe facilitates the visualization of the results, without requiring any other additional software, thanks to the inclusion of an HTML report output. The output includes several summary tables, a dynamic visualization of the retrieved interactions, along with some statistics for the retrieved references (Fig.1).

In conclusion, yet some similar tools have already been developed, PPaxe allows researchers both to perform large-scale text-mining, but also to analyze small and focused sets. The newly implemented range of output options and reports should make PPaxe a valuable tool for researchers to retrieve and curate novel PPIs described in the scientific literature.

## Acknowledgements

The authors are grateful to our beta tester users that played with the initial versions of the tool, especially to Rodrigo Arenas-Galnares, and to the referees for their useful comments.

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# Supplementary materials 

# PPaxe: easy extraction of protein occurrence and interactions from the scientific literature 

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## 1 PPaxe features

PPaxe uses three types of features: token distance measures between the entities in the sentence (e.g. from each candidate protein to each verb between them), POS tag composition (both between the candidate proteins and in their vicinity), and finally keyword occurrence in the sentences. This approach makes PPaxe capable of retrieving interactions that don't follow any particular structure or pattern, such as "Protein- $A$ binds Protein- $B$ ", "Protein- $A$ and Protein- $B$ interact.", and so on. All features are listed on Supplementary Materials Table S3.

## 2 PPaxe evaluation

Performance of the PPaxe estimated over the three datasets using 10-fold cross-validation, compared to previously published tools, is shown on Supplementary Materials Table S1. Quan et. al I and II correspond to the unsupervised and the semi-supervised methods described in that article respectively. The performance of PPaxe when it comes to retrieving interactions varies from dataset to dataset. Overall, PPaxe performed better than a previously described method on the same datasets (Zhao et al., 2016), slightly worse than a rule-based approach (Raja et al., 2013), and better and similarly to an unsupervised and a semi-supervised method respectively (Quan et al., 2014).

### 2.1 Performance metrics

$$
\begin{aligned}
& \text { Accuracy }=\frac{t p+t n}{t p+t n+f p+f n} \\
& \text { Precision }=\frac{t p}{t p+f p} \\
& \text { Recall }=\frac{t p}{t p+f n} \\
& F 1=2 \cdot \frac{\text { Precision } \cdot \text { Recall }}{\text { Precision }+ \text { Recall }}
\end{aligned}
$$

where:
tp is true positives.
tn is true negatives.
fp is false positives.
fn is false negatives.

### 2.2 BioGRID test case

PPaxe interaction extraction was compared against the interactions annotated in the BioGRID database. In order to do so, the following query was performed on PubMed:

```
protein protein interactions
    AND (hasabstract[text]
    AND "last 5 years"[PDat]
    AND Humans [Mesh])
```

That PubMed query returned 41,286 entries on October $17^{\text {th }}, 2018$. We picked up the first 2,000 PubMed identifiers for posterior analyses, after sorting them by decreasing publication date, to ensure retrieving the most recent papers that may contain novel interactions.

PPaxe retrieved 104 interactions ( 92 unique). From those interactions, 31 contained interactions already annotated in BioGRID, defined as "BioGRID positive" (valid sentence defining interactions already supported by BioGRID) and "BioGRID negative" (wrong sentences defining an interaction contained in BioGRID). We manually annotated the remaining 73 interactions as "PPaxe positive" (those sentences with a correct protein-protein or genetic interaction, according to the sentence alone) or "PPaxe negative" (interactions not supported by the sentence). The results of this annotation can be seen in Table S2.

Even though the comparison against BioGRID showed that most interactions retrieved by PPaxe were not annotated in the database, the manual annotation revealed that most of them were in fact described in the sentence: 40 out of the 73 sentences were annotated as "PPaxe positive". By considering both "BioGRID positive" and "PPaxe positive" together, $65.38 \%$ of the interactions retrieved by PPaxe can be considered correctly retrieved, which is slightly smaller than the estimated precision of interaction retrieval computed by 10-fold cross validation shown in Table S1.

We can't consider this test as a full assessment of PPaxe performance due to several limitations of this approach. For instance, we don't have a gold standard neither for sentences, nor interactions; we can't consider BioGRID as a full validated gold standard, and the annotation of the sentences was performed after their selection. Moreover, the impact of the protein/gene tagger can't be considered separately from the interaction extraction procedure as it has been done in the cross-validation tests. In summary, that implies we can't estimate some of the performance metrics such as the Recall to compare those results with the cross-validation assessment. Finally, the large number of correctly retrieved interactions by PPaxe that were not annotated in BioGRID could be explained by either differences in gene symbol normalization (although both sets of protein symbols were normalized using the HGNC alias dictionary), by the use of non-official gene names in the articles, or by the fact that the interactions are yet to be included in BioGRID.

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Quan, C. et al. (2014). An unsupervised text mining method for relation extraction from biomedical literature. PLoS ONE, 9, e102039.
Raja, K. et al. (2013). PPInterFinder - A mining tool for extracting causal relations on human proteins from literature. Database, 2013, bas052 (1-11).

Zhao, Z. et al. (2016). A protein - protein interaction extraction approach based on deep neural network. Int. J. Data Mining and Bioinformatics, 15(2), 145-164.

(b)



Figure S1: A larger view of manuscript Figure 1. a) PPaxe web application form, which allows users to both input PubMed identifiers directly or to write a PubMed query to retrieve the requested articles. b) Graph visualization made using Cytoscape.js from the HTML report of PPaxe. c) Sentences containing PPIs retrieved from the analysis of four PubMed abstracts (PMIDs: 15640847, 20729546, 25196150, and 25211495), presented in the HTML output as a searchable table. The Confidence value (shown in the table and on the graph edges) corresponds to the normalized percentage of votes of the predictor (ranging from 0 to 1 ).

Table S1: Assessment of PPaxe interaction extraction performance. PPaxe performance metrics were computed with a 10 -fold cross-validation for each dataset. The same procedure was not applied to the other tools, due to the inability to get the corresponding software to run under the same conditions. Therefore, the metrics displayed on this table were retrieved from their respective articles. "All sets" correspond to the validation run on a merged dataset built from the other three (AImed + BioInfer + LLL).

Tool Accuracy Precision Recall F1

|  | PPaxe | $\mathbf{8 0 . 0 7}$ | $\mathbf{7 0 . 5 4}$ | 50.93 | $\mathbf{5 9 . 1 5}$ |
| ---: | ---: | ---: | ---: | ---: | ---: |
|  | Zhao et. al | - | 50.51 | 63.38 | 56.12 |
| AImed | Quan et. al I | - | 44.80 | 71.40 | 55.10 |
|  | Quan et. al II | - | 56.6 | 66.80 | 60.7 |
|  | Raja et. al | - | 80.25 | 56.12 | 66.05 |
| BioInfer | PPaxe | $\mathbf{8 8 . 4 2}$ | $\mathbf{8 1 . 2 7}$ | $\mathbf{6 5 . 5 5}$ | $\mathbf{7 2 . 5 7}$ |
|  | Zhao et. al | - | 53.89 | 72.9 | 61.63 |
|  | PPaxe | $\mathbf{7 2 . 9 6}$ | $\mathbf{7 6 . 9 8}$ | $\mathbf{8 7 . 3 9}$ | $\mathbf{8 1 . 8 6}$ |
|  | Zhao et. al | - | 75.84 | 91.84 | 82.00 |
| All sets | PPaxe | $\mathbf{8 4 . 4 8}$ | $\mathbf{7 6 . 5 0}$ | $\mathbf{5 8 . 6 8}$ | $\mathbf{6 6 . 4 1}$ |

Table S2: PPaxe extracted interactions when intersecting them with those in BioGRID. The retrieved interactions were compared against the BioGRID database, and those not annotated in the database were manually curated. In blue, 28 interactions described in BioGRID ("BioGRID positive"); in yellow, 3 interactions described in BioGRID but annotated as incorrect after manual inspection ("BioGRID negative"); in green, 40 interactions not described in BioGRID but annotated as correct after manual curation ("PPaxe positive"); in red, 33 interactions not described in BioGRID annotated as incorrect ("PPaxe negative"). The "Conf." value corresponds to the normalized percentage of votes of the random forest classifier used by PPaxe.

| PMID | INT A | INT B | Conf. | Sentence after tokenization |
| :---: | :---: | :---: | :---: | :---: |
| 29899090 | TRIM41 <br> (TRIM41) | NP (ZNF384) | 0.796 | Here, we report that TRIM41 interacts with NP through its SPRY domain |
| 29444082 | S100B (S100B) | S100A1 (S100A1) | 0.676 | We found that S100B could interact with S100A1 via NMR 1H15N HSQC titrations |
| 29178343 | GRP78 (HSPA5) | PRDM14 <br> (PRDM14) | 0.644 | These results suggest that HSP90 and GRP78 interact with PRDM14 and participate in cancer regulation |
| 29220652 | PARP1 (TIPARP) | ALC1 (MYL4) | 0.627 | Its engagement with PARylated PARP1 activates ALC1 at sites of DNA damage, but the underlying mechanism remains unclear |
| 29358401 | $\begin{aligned} & \text { DNAAF2 } \\ & \text { (DNAAF2) } \end{aligned}$ | SPAG1 (SPAG1) | 0.564 | FRET analysis of HEAT domain deletions and human mutations showed that HEATR2 interacted with itself and SPAG1 at multiple HEAT domains, while DNAAF2 interacted with SPAG1 |
| 30111544 | REV7 (MAD2L2) | REV3 (REV3L) | 0.556 | Rev7 interacts with Rev3 by a mechanism conserved among HORMA proteins, whereby an open-to-closed transition locks the ligand underneath the " safety belt " loop |
| 29328377 | MYC (MYC) | CDK2 (CDK2) | 0.518 | The cyclindependent kinase inhibitor 1A (CDKN1A ), E2F transcription factor 1 ( E2F1 ), and MYC interacted with CDK2 |
| 29374759 | VDR (VDR) | P53 (TP53) | 0.480 | VDR binding to p53 was confirmed by western blot analysis |
| 30021902 | $\begin{aligned} & \text { CDC25A } \\ & \text { (CDC25A) } \end{aligned}$ | TBK1 (TBK1) | 0.458 | Further analysis indicated that Cdc25A can interact with TBK1 and reduce the phosphorylation of TBK1 at S172, which in turn decreases the phosphorylation of its downstream substrate IRF3 |
| 29281729 | IFITM3 (IFITM3) | LSD1 (KDM1A) | 0.458 | Our data suggest that the demethylation of IFITM3 by LSD1 is beneficial for the host to fight against RNA virus infection |
| 29684085 | KAT5 (KAT5) | CD4 (CD4) | 0.449 | The pro-latency effect of KAT5 is confirmed in a primary CD4 + T cell latency model as well as cells from ART-treated patients |
| 29295922 | PAK4 (PAK4) | CDC42 (CDC42) | 0.436 | Using solution scattering we find that the full-length PAK4 heterodimer with CDC42 adopts primarily a compact organization |
| 29154191 | CD11B (ITGAM) | RHO (RHOD) | 0.413 | Mechanistically, -synuclein bound to CD11b and subsequently activated Rho signaling pathway |
| 29295922 | CDC42 (CDC42) | PAK4 (PAK4) | 0.387 | These additional interactions modulate kinase activity and increase the binding affinity of CDC42 for full-length PAK4 compared with the CRIB domain alone |
| 30021902 | $\begin{aligned} & \mathrm{CDC} 25 \mathrm{~A} \\ & (\mathrm{CDC} 25 \mathrm{~A}) \end{aligned}$ | IRF3 (IRF3) | 0.382 | Consistently, knockdown of Cdc25A upregulates the phosphorylation of both TBK1-S172 and IRF3 in Sendai virus-infected or TBK1-transfected 293T cells |
| 29925658 | STAT1 (STAT1) | NSP2 (RTN2) | 0.378 | Chemically blocking CRM1-mediated nuclear export in the presence of nsP2 additionally showed that nuclear translocation of STAT1 is not affected by nsP2 |
| 29218693 | NCK2 (NCK2) | ITGB1 (ITGB1) | 0.373 | Co-IP showed that NCK2 can directly bind ITGB1, but not VEGFA |
| 29334217 | P53 (TP53) | HSP90 <br> (HSP90AA1) | 0.360 | The DNA-binding domain ( DBD ) of p53 is known to interact with the chaperone Hsp90, but the role of other members of the chaperone network, including co-chaperones such as p23, is unknown |
| 29295922 | CDC42 (CDC42) | PAK4 (PAK4) | 0.351 | We therefore show that the interaction of CDC42 with PAK4 can influence kinase activity in a previously unappreciated manner |
| 29358401 | HEATR2 <br> (DNAAF5) | SPAG1 (SPAG1) | 0.338 | FRET analysis of HEAT domain deletions and human mutations showed that HEATR2 interacted with itself and SPAG1 at multiple HEAT domains, while DNAAF2 interacted with SPAG1 |

Continued on next page

| PMID | INT A | INT B | Conf. | Sentence after tokenization |
| :---: | :---: | :---: | :---: | :---: |
| 29232376 | GCN5 (KAT2B) | CHE1 (BCHE) | 0.329 | In this study, we aimed to identify whether besides ADA3, other components of the HAT modules of SAGA and ATAC complexes human ADA2 and GCN5 also interact with Che-1 / AATF |
| 29379028 | NS1 (PTPN11) | TBK1 (TBK1) | 0.324 | This mutation enables NS1 binding to TBK1 and reduces TBK1 phosphorylation |
| 29184850 | CELLUGYRIN (SYNGR2) | CDTB (CDB2) | 0.324 | Furthermore, we demonstrate that cellugyrin is an intracellular binding partner for CdtB as demonstrated by immunoprecipitation |
| 29512721 | OSTEOCALCIN (BGLAP) | FOXO1 (FOXO1) | 0.311 | The HIF1induced expression of Runx2 and ALP may be completely dependent on the expression levels of Foxo1, and in turn osteocalcin may be partially dependent on Foxol expression |
| 29950413 | SOX2 (SOX2) | STAT3 (STAT3) | 0.307 | IE1 mediates SOX2 depletion by targeting STAT3, a critical upstream regulator of SOX2 expression |
| 29281729 | LSD1 (KDM1A) | IFITM3 (IFITM3) | 0.302 | We have found that LSD1 is recruited to demethylate IFITM3 at position K88 under IFN treatment |
| 29212519 | VEGF (VEGFA) | IGF1 (IGF1) | 0.298 | We found that a functional cooperation between HIF-1 and GPER is essential for the transcriptional activation of VEGF induced by IGF1 |
| 29178989 | NETS (SPINK5) | FSAP (HABP2) | 0.298 | Taken together, NETs bind to FSAP, but do not activate proFSAP unless histones are released from NETs by DNAse |
| 29743362 | FUBP1 (FUBP1) | P53 (TP53) | 0.284 | Here we report that human adenovirus 5 coopts the cellular protein FUBP1 to prevent the activation of the p53 stress response pathway that would block viral replication |
| 29152905 | L13A (RPL13A) | EIF4G (EIF4G1) | 0.280 | EPRS binds the GAIT element in target mRNAs, NSAP1 negatively regulates mRNA binding, L13a binds eIF4G to block ribosome recruitment, and GAPDH shields L13a from proteasomal degradation |
| 29899107 | MDA5 (IFIH1) | IFN (IFNA1) | 0.271 | Although RIG-I has been recognized as the leading cytoplasmic sensor against HCV for a long time, recent findings that MDA5 regulates the IFN response to HCV have emerged |
| 29665350 | PXR (NR1I2) | CYP3A4 <br> (CYP3A4) | 0.262 | In conclusion, PXR activation and PXR-mediated induction of CYP3A4 expression by PAs seem to be structure-dependent |
| 29669839 | GP (RNF130) | $\begin{aligned} & \text { TETHERIN } \\ & \text { (BST2) } \end{aligned}$ | 0.258 | To our knowledge, these findings demonstrate for the first time that GP can antagonize tetherin in infected cells and provide a tool to study the impact of GP-dependent tetherin counteraction on EBOV spread |
| 29232376 | GCN5 (KAT2B) | AATF (AATF) | 0.258 | In this study, we aimed to identify whether besides ADA3, other components of the HAT modules of SAGA and ATAC complexes human ADA2 and GCN5 also interact with Che-1 / AATF |
| 29660231 | S100A4 (S100A4) | P53 (TP53) | 0.253 | Wnt / -catenin targets, c-MYC and S100A4 were upregulated in p53 cells and were downregulated when plakoglobin was coexpressed |
| 29690653 | VEGFA (VEGFA) | VEGFR2 (KDR) | 0.218 | Although VEGF-A ligands bind to both VEGFR1 and VEGFR2 they primarily signal via VEGFR2 leading to endothelial cell proliferation, survival, migration and vascular permeability |
| 29925821 | RHOA (RHOA) | RAC1 (RNASE1) | 0.213 | All genetic evidences indicate that in these disorders the RhoA pathway is hyperactive while the Rac1 and cdc42 pathways are consistently hypoactive |
| 29690653 | VEGFA (VEGFA) | VEGFR1 (FLT1) | 0.213 | Although VEGF-A ligands bind to both VEGFR1 and VEGFR2 , they primarily signal via VEGFR2 leading to endothelial cell proliferation, survival, migration and vascular permeability |
| 29212519 | GPER (GPER1) | VEGF (VEGFA) | 0.204 | We found that a functional cooperation between HIF-1 and GPER is essential for the transcriptional activation of VEGF induced by IGF1 |
| 29444113 | KCNQ1 (KCNQ1) | KCNE1 (KCNE1) | 0.200 | The results reveal that interactions between KCNQ1 with KCNE1 causes a pore constriction in the former, which in-turn forms small energetic barriers in the ion-permeation pathway |
| 30111544 | REV7 (MAD2L2) | REV1 (REV1) | 0.196 | We demonstrate that Rev7 uses the conventional HORMA dimerization interface both to form a homodimer when tethered by the two RBMs in Rev3 and to heterodimerize with other HORMA domains, Mad2 and p31 Structurally, the Rev7 dimer can bind only one copy of Rev1, revealing an unexpected Rev1/Pol architecture |
| 29677136 | NOP53 (NOP53) | RIGI (DDX58) | 0.182 | Cytoplasmic NOP53 interacts with the retinoic acid-inducible gene I ( RIG-I ) to remove its K63-linked ubiquitination, leading to attenuation of type I interferon IFN- |


| PMID | INT A | INT B | Conf. | Sentence after tokenization |
| :---: | :---: | :---: | :---: | :---: |
| 29269420 | L1 (IGKV116) | CENPA (CENPA) | 0.182 | We show that human CENP-N confers binding specificity through interactions with the L1 loop of CENP-A, stabilized by electrostatic interactions with the nucleosomal DNA |
| 29690653 | VEGFA (VEGFA) | VEGFR2 (KDR) | 0.178 | This review explores the molecular pharmacology of VEGF-A isoforms at VEGFR2 in respect to ligand binding and downstream signalling |
| 29167311 | AND1 (WDHD1) | CTF4 (WDHD1) | 0.178 | AND-1 has maintained the trimeric structure of yeast Ctf4, driven by its conserved SepB domain |
| 29925658 | NSP2 (RTN2) | IFN (IFNA1) | 0.173 | The research described here specifies where in the JAK/STAT signaling cascade the IFN response is inhibited and which protein domain of nsP2 is responsible for IFN inhibition |
| 29207260 | E2F1 (E2F1) | TEAD1 (TEAD1) | 0.173 | Further, we found that human E2F1 competes with YAP for TEAD1 binding, affecting YAP activity, indicating that this mode of cross-regulation is conserved |
| 29444113 | KCNE1 (KCNE1) | KCNQ1 (KCNQ1) | 0.169 | These findings correlate with the previous experimental reports that interactions of KCNE1 dramatically slows the activation of KCNQ1 |
| 29297316 | CCR5 (CCR5) | CD4 (CD4) | 0.169 | It was found that the subnetworks formed by CCR5 and IFNAR1 and their neighbors were a fragments of two key pathways functioning during the course of tick-borne encephalitis : (1) the attenuation of interferon-I signaling pathway by the TBEV NS5 protein that targeted peptidase D ; (2) proinflammation and tissue damage pathway triggered by chemokine receptor CCR5 interacting with CD4, CCL3, CCL4, CCL2 |
| 29669839 | GP (RNF130) | $\begin{aligned} & \text { TETHERIN } \\ & \text { (BST2) } \end{aligned}$ | 0.160 | Moreover , they provide the first evidence that GP can antagonize tetherin in the context of an infectious EBOV surrogate |
| 29321315 | RIGI (DDX58) | TRIM25 (TRIM25) | 0.151 | We report interactions between the Nipah virus V protein and both RIG-I regulatory protein TRIM25 and RIG-I |
| 29471045 | PRDM14 <br> (PRDM14) | HOXA1 (HOXA1) | 0.147 | Here, we confirm PRDM14 is an interactor of HOXA1 and we identify the homeodomain of HOXA1 as well as the PR domain and Zinc fingers of PRDM14 to be required for the interaction |
| 29367244 | ATG12 (ATG12) | ATG5 (ATG5) | 0.147 | A close inspection of the HBV/autophagy cross talk revealed that the virus depended on Atg12 covalently conjugated to Atg5 |
| 29760086 | STIM1 (STIM1) | ORAI1 (ORAI1) | 0.138 | Store-operated Orai1 channels are activated through a unique inside-out mechanism involving binding of the endoplasmic reticulum Ca sensor STIM1 to cytoplasmic sites on Orai1 |
| 29549180 | P53 (TP53) | MDM2 (MDM2) | 0.133 | In unstressed cells, p53 is normally held in check by MDM2 that targets p53 for transcriptional repression, proteasomal degradation, and cytoplasmic localization |
| 29614078 | GDNF (GDNF) | AP1 (JUND) | 0.124 | GDNF stimulates MAP kinase, activating the transcription factors SRF and AP-1 |
| 29512721 | ALP (SLPI) | FOXO1 (FOXO1) | 0.116 | The HIF1induced expression of Runx2 and ALP may be completely dependent on the expression levels of Foxo1, and in turn osteocalcin may be partially dependent on Foxol expression |
| 29734338 | RIT1 (RIT1) | RAC1 (RNASE1) | 0.111 | We found RIT1 also to directly interact with the RHO GTPases CDC42 and RAC1, both of which are crucial regulators of actin dynamics upstream of PAK1 |
| 29232376 | ADA2 (TADA2A) | AATF (AATF) | 0.111 | In this study, we aimed to identify whether besides ADA3, other components of the HAT modules of SAGA and ATAC complexes , human ADA2 and GCN5 also interact with Che-1 / AATF |
| 30021902 | $\begin{aligned} & \text { CDC25A } \\ & (\mathrm{CDC} 25 \mathrm{~A}) \end{aligned}$ | TBK1 (TBK1) | 0.107 | These results demonstrate that Cdc25A inhibits the antiviral immune response by reducing the active form of TBK1 |
| 29339503 | $\begin{aligned} & \text { BTN3A2 } \\ & \text { (BTN3A2) } \end{aligned}$ | BTN3A1 <br> (BTN3A1) | 0.107 | Addressing this paradox, we show that BTN3A2 regulates the subcellular localization of BTN3A1, including functionally important associations with the endoplasmic reticulum (ER ), and is specifically required for optimal BTN3A1-mediated activation of V 9 V 2 T cells |
| 29328377 | E2F1 (E2F1) | CDK2 (CDK2) | 0.107 | The cyclindependent kinase inhibitor 1A (CDKN1A ), E2F transcription factor 1 ( E2F1), and MYC interacted with CDK2 |
| 30181274 | RAB5 (RAB5A) | RABGAP5 (SGSM3) | 0.102 | Thus , binding of Etf-2 to RAB5-GTP appears to delay RAB5 inactivation by impeding RABGAP5 localization to endosomes |
| 29899144 | LPL (LPL) | $\begin{aligned} & \text { GPIHBP1 (GPI- } \\ & \text { HBP1) } \end{aligned}$ | 0.102 | Third, we show that LPL accumulates near capillary endothelial cells even in the absence of GPIHBP1 |
| 29949917 | DDX6 (DDX6) | RIGI (DDX58) | 0.098 | These findings imply a novel function for DDX6 as an RNA cosensor and signaling enhancer for RIG-I |

Continued on next page

|  | INT B | Conf. | Sentence after tokenization |
| :--- | :--- | :--- | :--- |
| 29949917 | INT A | DDX6 (DDX6) | RIGI (DDX58) | $0^{0.098}$| Notably, DDX6 was found to bind viral RNA capable to stimulate |
| :--- |
| RIG-I |

Continued on next page

| PMID | INT A | Conf. | Sentence after tokenization |
| :--- | :--- | :--- | :--- | :--- |

Table S3: PPaxe features.

Feature name
TOK_DIST
TOTAL_TOK
BETWEEN_VB_COUNT BETWEEN_VBD_COUNT BETWEEN_VBG_COUNT BETWEEN_VBN_COUNT BETWEEN_VBP_COUNT BETWEEN_VBZ_COUNT BETWEEN_VERB_MAXSCORE BETWEEN_VERB_TOTALSCORE

BETWEEN_VERB_CLOSEST_DIST_A BETWEEN_VERB_FARTHEST_DIST_A BETWEEN_VERB_CLOSEST_DIST_B BETWEEN_VERB_FARTHEST_DIST_B ALL_VB_COUNT ALL_VBD_COUNT ALL_VBG_COUNT ALL_VBN_COUNT ALL_VBP_COUNT ALL_VBZ_COUNT ALL_VERB_MAXSCORE ALL_VERB_TOTALSCORE
ALL_VERB_CLOSEST_DIST_A ALL_VERB_FARTHEST_DIST_A ALL_VERB_CLOSEST_DIST_B ALL_VERB_FARTHEST_DIST_B BETWEEN_POS_2AP BETWEEN_POS_1AP BETWEEN_POS_COMMA BETWEEN_POS_LRB BETWEEN_POS_RRB BETWEEN_POS_DOT BETWEEN_POS_COLON BETWEEN_POS_CC BETWEEN_POS_CD BETWEEN_POS_DT BETWEEN_POS_EX BETWEEN_POS_FW BETWEEN_POS_IN BETWEEN_POS_JJ BETWEEN_POS_JJR BETWEEN_POS_JJS BETWEEN_POS_LS BETWEEN_POS_MD

## Description

Token distance between ProtA and ProtB.
Number of Tokens in sentence.
Number of Tokens tagged as VB between ProtA and ProtB.
Number of Tokens tagged as VBD between ProtA and ProtB.
Number of Tokens tagged as VBG between ProtA and ProtB.
Number of Tokens tagged as VBN between ProtA and ProtB.
Number of Tokens tagged as VBP between ProtA and ProtB.
Number of Tokens tagged as VBZ between ProtA and ProtB.
Higher score for verbs between ProtA and ProtB.
Sum of verb scores between ProtA and ProtB.
Token distance to closer verb to ProtA located between ProtA and ProtB. Token distance to farthest verb to ProtA located between ProtA and ProtB.

Token distance to closer verb to ProtB located between ProtA and ProtB.
Token distance to farthest verb to ProtB located between ProtA and ProtB.
Total number of Tokens tagged as VB in sentence.
Total number of Tokens tagged as VBD in sentence.
Total number of Tokens tagged as VBG in sentence.
Total number of Tokens tagged as VBN in sentence.
Total number of Tokens tagged as VBP in sentence.
Total number of Tokens tagged as VBZ in sentence.
Higher scoring verb in sentence.
Sum of verb scores in sentence.
Token distance to closer verb to ProtA in sentence.
Token distance to farthest verb to ProtA in sentence.
Token distance to closer verb to ProtB in sentence.
Token distance to farthest verb to ProtB in sentence.
Number of Tokens tagged as 2AP between ProtA and ProtB.
Number of Tokens tagged as 1AP between ProtA and ProtB.
Number of Tokens tagged as COMMA between ProtA and ProtB.
Number of Tokens tagged as LRB between ProtA and ProtB.
Number of Tokens tagged as RRB between ProtA and ProtB.
Number of Tokens tagged as DOT between ProtA and ProtB.
Number of Tokens tagged as COLON between ProtA and ProtB.
Number of Tokens tagged as CC between ProtA and ProtB.
Number of Tokens tagged as CD between ProtA and ProtB.
Number of Tokens tagged as DT between ProtA and ProtB.
Number of Tokens tagged as EX between ProtA and ProtB.
Number of Tokens tagged as FW between ProtA and ProtB.
Number of Tokens tagged as IN between ProtA and ProtB.
Number of Tokens tagged as JJ between ProtA and ProtB.
Number of Tokens tagged as JJR between ProtA and ProtB.
Number of Tokens tagged as JJS between ProtA and ProtB.
Number of Tokens tagged as LS between ProtA and ProtB.
Number of Tokens tagged as MD between ProtA and ProtB.

Feature name Description

BETWEEN_POS_NN BETWEEN_POS_NNP BETWEEN_POS_NNPS BETWEEN_POS_NNS BETWEEN_POS_PDT BETWEEN_POS_POS BETWEEN_POS_PRP BETWEEN_POS_PRP_DOLAR BETWEEN_POS_RB BETWEEN_POS_RBR BETWEEN_POS_RBS BETWEEN_POS_RP BETWEEN_POS_SYM BETWEEN_POS_TO BETWEEN_POS_UH BETWEEN_POS_VB BETWEEN_POS_VBD BETWEEN_POS_VBG BETWEEN_POS_VBN BETWEEN_POS_VBP BETWEEN_POS_VBZ BETWEEN_POS_WDT BETWEEN_POS_WP BETWEEN_POS_WP_DOLAR BETWEEN_POS_WRB

ALL_POS_2AP
ALL_POS_1AP
ALL_POS_COMMA
ALL_POS_LRB
ALL_POS_RRB
ALL_POS_DOT
ALL_POS_COLON ALL_POS_CC
ALL_POS_CD
ALL_POS_DT
ALL_POS_EX
ALL_POS_FW
ALL_POS_IN
ALL_POS_JJ
ALL_POS_JJR
ALL_POS_JJS
ALL_POS_LS
ALL_POS_MD
ALL_POS_NN
ALL_POS_NNP
ALL_POS_NNPS

Number of Tokens tagged as NN between ProtA and ProtB.
Number of Tokens tagged as NNP between ProtA and ProtB.
Number of Tokens tagged as NNPS between ProtA and ProtB.
Number of Tokens tagged as NNS between ProtA and ProtB.
Number of Tokens tagged as PDT between ProtA and ProtB.
Number of Tokens tagged as POS between ProtA and ProtB.
Number of Tokens tagged as PRP between ProtA and ProtB.
Number of Tokens tagged as PRP_DOLAR between ProtA and ProtB.
Number of Tokens tagged as RB between ProtA and ProtB.
Number of Tokens tagged as RBR between ProtA and ProtB.
Number of Tokens tagged as RBS between ProtA and ProtB.
Number of Tokens tagged as RP between ProtA and ProtB.
Number of Tokens tagged as SYM between ProtA and ProtB.
Number of Tokens tagged as TO between ProtA and ProtB.
Number of Tokens tagged as UH between ProtA and ProtB.
Number of Tokens tagged as VB between ProtA and ProtB.
Number of Tokens tagged as VBD between ProtA and ProtB.
Number of Tokens tagged as VBG between ProtA and ProtB.
Number of Tokens tagged as VBN between ProtA and ProtB.
Number of Tokens tagged as VBP between ProtA and ProtB.
Number of Tokens tagged as VBZ between ProtA and ProtB.
Number of Tokens tagged as WDT between ProtA and ProtB.
Number of Tokens tagged as WP between ProtA and ProtB.
Number of Tokens tagged as WP_DOLAR between ProtA and ProtB.
Number of Tokens tagged as WRB between ProtA and ProtB.
Number of Tokens tagged as 2AP in sentence.
Number of Tokens tagged as 1AP in sentence.
Number of Tokens tagged as COMMA in sentence.
Number of Tokens tagged as LRB in sentence.
Number of Tokens tagged as RRB in sentence.
Number of Tokens tagged as DOT in sentence.
Number of Tokens tagged as COLON in sentence.
Number of Tokens tagged as CC in sentence.
Number of Tokens tagged as CD in sentence.
Number of Tokens tagged as DT in sentence.
Number of Tokens tagged as EX in sentence.
Number of Tokens tagged as FW in sentence.
Number of Tokens tagged as IN in sentence.
Number of Tokens tagged as JJ in sentence.
Number of Tokens tagged as JJR in sentence.
Number of Tokens tagged as JJS in sentence.
Number of Tokens tagged as LS in sentence.
Number of Tokens tagged as MD in sentence.
Number of Tokens tagged as NN in sentence.
Number of Tokens tagged as NNP in sentence.
Number of Tokens tagged as NNPS in sentence.

Feature name Description

## ALL_POS_NNS

 ALL_POS_PDT ALL_POS_POS ALL_POS_PRPALL_POS_PRP_DOLAR ALL_POS_RB ALL_POS_RBR ALL_POS_RBS ALL_POS_RP
ALL_POS_SYM
ALL_POS_TO ALL_POS_UH ALL_POS_VB

ALL_POS_VBD
ALL_POS_VBG
ALL_POS_VBN
ALL_POS_VBP ALL_POS_VBZ ALL_POS_WDT ALL_POS_WP

ALL_POS_WP_DOLAR ALL_POS_WRB
BETWEEN_PROTA_COUNT BETWEEN_PROTB_COUNT ALL_PROTA_COUNT ALL_PROTB_COUNT
KEYWORD_COUNT_acetylate KEYWORD_COUNT_activate KEYWORD_COUNT_acylate
KEYWORD_COUNT_amidate KEYWORD_COUNT_assemble KEYWORD_COUNT_attach KEYWORD_COUNT_bind KEYWORD_COUNT_biotinylate KEYWORD_COUNT_block KEYWORD_COUNT_brominate KEYWORD_COUNT_carboxylate KEYWORD_COUNT_catalyze KEYWORD_COUNT_cleave KEYWORD_COUNT_complex KEYWORD_COUNT_conjugate KEYWORD_COUNT_contact KEYWORD_COUNT_couple KEYWORD_COUNT_cysteinylate KEYWORD_COUNT_demethylate KEYWORD_COUNT_dephosphorylate

Number of Tokens tagged as NNS in sentence.
Number of Tokens tagged as PDT in sentence.
Number of Tokens tagged as POS in sentence.
Number of Tokens tagged as PRP in sentence.
Number of Tokens tagged as PRP_DOLAR in sentence.
Number of Tokens tagged as RB in sentence.
Number of Tokens tagged as RBR in sentence.
Number of Tokens tagged as RBS in sentence.
Number of Tokens tagged as RP in sentence.
Number of Tokens tagged as SYM in sentence.
Number of Tokens tagged as TO in sentence.
Number of Tokens tagged as UH in sentence.
Number of Tokens tagged as VB in sentence.
Number of Tokens tagged as VBD in sentence.
Number of Tokens tagged as VBG in sentence.
Number of Tokens tagged as VBN in sentence.
Number of Tokens tagged as VBP in sentence.
Number of Tokens tagged as VBZ in sentence.
Number of Tokens tagged as WDT in sentence.
Number of Tokens tagged as WP in sentence.
Number of Tokens tagged as WP_DOLAR in sentence.
Number of Tokens tagged as WRB in sentence.
Number of times ProtA appears between ProtA and ProtB.
Number of times ProtB appears between ProtA and ProtB.
Number of times ProtA appears in sentence.
Number of times ProtB appears in sentence.
Number of times 'acetylate' appears between ProtA and ProtB.
Number of times 'activate' appears between ProtA and ProtB.
Number of times 'acylate' appears between ProtA and ProtB.
Number of times 'amidate' appears between ProtA and ProtB.
Number of times 'assemble' appears between ProtA and ProtB.
Number of times 'attach' appears between ProtA and ProtB.
Number of times 'bind' appears between ProtA and ProtB.
Number of times 'biotinylate' appears between ProtA and ProtB.
Number of times 'block' appears between ProtA and ProtB.
Number of times 'brominate' appears between ProtA and ProtB.
Number of times 'carboxylate' appears between ProtA and ProtB.
Number of times 'catalyze' appears between ProtA and ProtB.
Number of times 'cleave' appears between ProtA and ProtB.
Number of times 'complex' appears between ProtA and ProtB.
Number of times 'conjugate' appears between ProtA and ProtB.
Number of times 'contact' appears between ProtA and ProtB.
Number of times 'couple' appears between ProtA and ProtB.
Number of times 'cysteinylate' appears between ProtA and ProtB.
Number of times 'demethylate' appears between ProtA and ProtB.
Number of times 'dephosphorylate' appears between ProtA and ProtB.

Feature name
KEYWORD_COUNT_dimerise KEYWORD_COUNT_dimerize KEYWORD_COUNT_disassemble KEYWORD_COUNT_discharge KEYWORD_COUNT_dissociate
KEYWORD_COUNT_down-regulate KEYWORD_COUNT_downregulate KEYWORD_COUNT_farnesylate KEYWORD_COUNT_formylate KEYWORD_COUNT_hydroxilate KEYWORD_COUNT_hydroxylate KEYWORD_COUNT_inactivate KEYWORD_COUNT_induce KEYWORD_COUNT_inhibit KEYWORD_COUNT_interact KEYWORD_COUNT_mediate KEYWORD_COUNT_methylate KEYWORD_COUNT_modify KEYWORD_COUNT_modulate KEYWORD_COUNT_multimerise KEYWORD_COUNT_multimerize KEYWORD_COUNT_myristoylate KEYWORD_COUNT_myristylate KEYWORD_COUNT_nitrosylate KEYWORD_COUNT_overexpress KEYWORD_COUNT_palmitoylate KEYWORD_COUNT_palmitylate KEYWORD_COUNT_phosphorylate KEYWORD_COUNT_precipitate KEYWORD_COUNT_promote KEYWORD_COUNT_pyruvate KEYWORD_COUNT_regulate
KEYWORD_COUNT_repress KEYWORD_COUNT_stimulate KEYWORD_COUNT_substitute KEYWORD_COUNT_sumoylate KEYWORD_COUNT_suppress KEYWORD_COUNT_transactivate
KEYWORD_COUNT_ubiquitinate KEYWORD_COUNT_ubiquitinylate KEYWORD_COUNT_up-regulate KEYWORD_COUNT_upregulate

Description
Number of times 'dimerise' appears between ProtA and ProtB.
Number of times 'dimerize' appears between ProtA and ProtB.
Number of times 'disassemble' appears between ProtA and ProtB.
Number of times 'discharge' appears between ProtA and ProtB. Number of times 'dissociate' appears between ProtA and ProtB.

Number of times 'down-regulate' appears between ProtA and ProtB.
Number of times 'downregulate' appears between ProtA and ProtB.
Number of times 'farnesylate' appears between ProtA and ProtB.
Number of times 'formylate' appears between ProtA and ProtB.
Number of times 'hydroxilate' appears between ProtA and ProtB.
Number of times 'hydroxylate' appears between ProtA and ProtB.
Number of times 'inactivate' appears between ProtA and ProtB.
Number of times 'induce' appears between ProtA and ProtB.
Number of times 'inhibit' appears between ProtA and ProtB.
Number of times 'interact' appears between ProtA and ProtB.
Number of times 'mediate' appears between ProtA and ProtB.
Number of times 'methylate' appears between ProtA and ProtB.
Number of times 'modify' appears between ProtA and ProtB.
Number of times 'modulate' appears between ProtA and ProtB.
Number of times 'multimerise' appears between ProtA and ProtB.
Number of times 'multimerize' appears between ProtA and ProtB.
Number of times 'myristoylate' appears between ProtA and ProtB.
Number of times 'myristylate' appears between ProtA and ProtB.
Number of times 'nitrosylate' appears between ProtA and ProtB.
Number of times 'overexpress' appears between ProtA and ProtB.
Number of times 'palmitoylate' appears between ProtA and ProtB.
Number of times 'palmitylate' appears between ProtA and ProtB.
Number of times 'phosphorylate' appears between ProtA and ProtB.
Number of times 'precipitate' appears between ProtA and ProtB.
Number of times 'promote' appears between ProtA and ProtB.
Number of times 'pyruvate' appears between ProtA and ProtB.
Number of times 'regulate' appears between ProtA and ProtB.
Number of times 'repress' appears between ProtA and ProtB.
Number of times 'stimulate' appears between ProtA and ProtB.
Number of times 'substitute' appears between ProtA and ProtB.
Number of times 'sumoylate' appears between ProtA and ProtB.
Number of times 'suppress' appears between ProtA and ProtB.
Number of times 'transactivate' appears between ProtA and ProtB.
Number of times 'ubiquitinate' appears between ProtA and ProtB.
Number of times 'ubiquitinylate' appears between ProtA and ProtB.
Number of times 'up-regulate' appears between ProtA and ProtB.
Number of times 'upregulate' appears between ProtA and ProtB.

