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Abstract: Interactions between proteins and small molecules are an integral part of biological processes in living organisms. Information on these interactions is dispersed over many databases, texts and prediction methods, which makes it difficult to get a comprehensive overview of the available evidence. To address this, we have developed STITCH (‘Search Tool for Interacting Chemicals’) that integrates these disparate data sources for 430 000 chemicals into a single, easy-to-use resource. In addition to the increased scope of the database, we have implemented a new network view that gives the user the ability to view binding affinities of chemicals in the interaction network. This enables the user to get a quick overview of the potential effects of the chemical on its interaction partners. For each organism, STITCH provides a global network; however, not all proteins have the same pattern of spatial expression. Therefore, only a certain subset of interactions can occur simultaneously. In the new, fifth release of STITCH, we have implemented functionality to filter out the proteins and chemicals not associated with a given tissue. The STITCH database can be downloaded in full, accessed programmatically via an extensive API, or searched via a redesigned web interface at http://stitch.embl.de.

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STITCH 5: augmenting protein–chemical interaction networks with tissue and affinity data

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ABSTRACT

Interactions between proteins and small molecules are an integral part of biological processes in living organisms. Information on these interactions is dispersed over many databases, texts and prediction methods, which makes it difficult to get a comprehensive overview of the available evidence. To address this, we have developed STITCH (‘Search Tool for Interacting Chemicals’) that integrates these disparate data sources for 430 000 chemicals into a single, easy-to-use resource. In addition to the increased scope of the database, we have implemented a new network view that gives the user the ability to view binding affinities of chemicals in the interaction network. This enables the user to get a quick overview of the potential effects of the chemical on its interaction partners. For each organism, STITCH provides a global network; however, not all proteins have the same pattern of spatial expression. Therefore, only a certain subset of interactions can occur simultaneously. In the new, fifth release of STITCH, we have implemented functionality to filter out the proteins and chemicals not associated with a given tissue. The STITCH database can be downloaded in full, accessed programmatically via an extensive API, or searched via a redesigned web interface at http://stitch.embl.de.

INTRODUCTION

The role of small molecules in biological systems can be understood only in the relation to the function of the targeted biomolecules, which, in turn, is largely defined by their interaction partners (1–3). The role of the interaction network is even more prominent in the area of the drug development, since diseases are often a consequence of multiple changes in the same pathway or protein complex (4,5). Taking into account the neighborhood of the targeted proteins and the topology of the network itself can lead to a better understanding of a drug’s cellular impact (6,7). Furthermore, as only a subset of all proteins are viable drug targets (8), most therapeutics target proteins in the network vicinity from more prospective, but undruggable, proteins (7). Several databases provide proteome-wide protein–chemical interactions (9–11) and several other (12–14) put protein–chemical interactions in the context of protein–protein interaction networks, which is essential for effective in silico drug discovery.

A drug’s impact on the organism and its efficacy depend on its engagement with the targeted proteins and the extent to which it disrupts the protein–protein and protein–chemical interaction network (7,15). This is related to the concentration of the drug, the strength with which it modulates the activity of the target, and the distribution of target proteins among different tissues (16). To enable the users to rationally select possible drug targets, we have added two new features to STITCH: a new mode that allows users to show known binding affinities between proteins and chemicals, and the ability to filter the network to show only proteins related to a selected tissue. STITCH, in its fifth release, shares protein space with STRING v10 (17) and now encompasses more than 9 600 000 proteins from 2031 eukaryotic and prokaryotic genomes. Also, its chemical space grew by a quarter compared to the previous version (18), from 340 000 to 430 000 compounds (not including different stereoisomers). STITCH is available through new redesigned web interface at http://stitch.embl.de and via an extensive API that al-

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zymes or receptors are among the most studied classes of small molecules that activate or inhibit proteins such as enzymes or receptors are among the most studied classes of exogenous small molecules. In order to assess the effect and confidence of protein–ligand binding, as well as variability in the affinity of known ligands, it is essential to know the binding affinity between the compound and its target. Usually, this binding affinity is quantified as the inhibition constant $K_i$. In some cases, $K_i$ values are not available, but other values such as the IC$_{50}$ or EC$_{50}$ (half of the maximal inhibitory concentration) can serve as an approximation. $K_i$ values of drugs vary greatly, from nanomolar inhibition constants to relatively high values, such as 52 $\mu$M between aspirin and cyclooxygenase 2 (27). Therefore, for any given drug, it is not so much the absolute value of the $K_i$, but rather the relative binding affinities that determine the impact on the interaction network.

In previous versions of STITCH, $K_i$ values from primary sources (27,28) were accessible to the user through the web-interface. In the new release of STITCH, the user can now choose to switch the network view to show the binding affinities of all protein–chemical interactions for which this value is known (Figure 1). This new network view is similar to the STITCH’s confidence view: the thickness of the edge between nodes scales with the $K_i$ value. If a $K_i$ is not available, IC$_{50}$ or EC$_{50}$ will be used to determine the depicted strength of the interaction. If there are multiple measurements available, the lowest value (i.e. highest reported affinity) will be used to determine the thickness of the edge.

**DATA AND FILTERING FOR TISSUE SPECIFICITY**

The protein–chemical network in STITCH is global and as such considers interactions anywhere in an organism. However, in multicellular organisms such as humans, not all proteins are present in every tissue. STITCH 5 addresses this through a new feature that allows users to filter a human interaction network so that only the proteins believed to be present in a specified tissue are shown (Figure 2). To provide this feature, STITCH now integrates tissue-specific protein expression patterns from two data sources. First, the TISSUES resource (33), which combines evidence from UniProt annotations, systematic large-scale transcriptomics and proteomics studies, and co-occurrence text mining. For use in STITCH, the text-mining evidence was recomputed based on the same texts used elsewhere in STITCH. Second, STITCH incorporates baseline expression patterns from tissues deposited in the Expression Atlas (34). Before augmenting the network with tissues data, users have to choose if they want to use data from TISSUES or Expression Atlas. The TISSUES resource contains confidence levels ranging from one (lowest confidence) to five (highest confidence). Accordingly, on the STITCH website users can select a tissue and a minimum confidence level. In contrast, datasets from the Expression Atlas are transformed into percentiles. The confidence score for a protein–protein interaction in the given tissue is then multiplied with the geometric mean of the two proteins’ expression percentiles. For protein–chemical interactions, the confidence score is multiplied with the protein’s expression percentile. To access the tissue expression patterns, users can search for tissues either by typing parts of the tissue names or by selecting a tissue from a list. Then, users can submit the changed settings to STITCH. In return, an updated network will be...
Figure 1. Display of binding affinities. The user interface of STITCH has been updated and the option to scale edge width of protein–chemical interactions according to binding affinity has been added. The shown network of multiple NSAIDs makes their different binding affinities clear: for example, aspirin has relatively low binding affinities, whereas rofecoxib is specifically binding PTGS2.

shown. As non-expressed nodes are removed (using TISSUES) or confidence values get updated (using Expression Atlas), other interaction partners may become part of the network.

USE CASES

STITCH has been widely used for a variety of different purposes. These fall into three broad classes: (i) small- to medium-scale analyses performed via the web interface, (ii) large-scale analyses that make use of the bulk download files and (iii) reuse of data from STITCH for development of new web-based resources.

Work by O’Reilly et al. on identifying potential drug targets for α1-antitrypsin deficiency exemplifies the web-based usage (35). Through a genome-wide RNAi screen in a Caenorhabditis elegans disease model, the authors identified 104 C. elegans genes of interest (having 85 human orthologs). To validate these as potential drug targets, the authors queried STITCH and MetaCore for each of the human proteins and thereby identified a compounds for use in follow-up experiments. Conversely, STITCH can also be queried for a set of chemicals to identify possible targets, as exemplified by the screen by Kumar et al. of compounds capable of altering intracellular manganese levels (36). The ability to see binding affinities in the new web interface makes STITCH 5 even better suited for such use cases than previous versions.

STITCH is also commonly used for large-scale analyses, which we facilitate by making the data available for bulk download. Ligeti et al. used these files to construct a network neighborhood of proteins around each drug and showed that the neighborhood overlap of two drugs can
predict synergy of drug combinations (37). On a related note, Vogt et al. made use of both the drug thesaurus and the protein-chemical interaction from STITCH to predict drug contraindications (38).

Last, but not least, the integrated data provided by STITCH is useful to researchers who develop their own web resources and prediction methods. An example of this is the ChemDIS resource, which combines the protein-chemical interactions from STITCH with tools for gene enrichment analysis to link chemicals via proteins to GO terms, pathways and diseases (39). The experimental protein-chemical interactions from STITCH are also sometimes used as a benchmark set when developing prediction methods as exemplified by Zhou et al. (40).

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