A Survey on Conditional Protein Generation Using Diffusion Models

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ABSTRACT

Proteins, essential to life, exhibit diverse functions shaped by their complex structures of amino acids. Malfunctioning proteins contribute to diseases, while engineered proteins offer potential medical and industrial benefits. However, the vast protein search space poses challenges in effective design tools. Computational methods, particularly the generative diffusion models, have emerged as promising tools for protein design. This survey explores how conditional generation within diffusion models facilitates tailored protein properties, guiding the design process towards specific outcomes. Conditioning plays a crucial role in shaping these outcomes, offering potential in targeted therapeutics and industrial applications. The survey covers foundational concepts, conditional settings, recent advancements, and future directions in protein design within diffusion models.

1 INTRODUCTION

Proteins are a ubiquitous and essential tool for any living organism. These intricate biomolecules, comprised of amino acids, fold into unique, complex structures. Proteins take part in numerous biological processes such as catalysing metabolic reactions, aiding the immune system, or adding structure to cells. On the contrary, misfolded or malfunctioning proteins can cause various diseases such as Alzheimer's, Parkinson's, and Huntington's disease.

Proteins are composed of repeating monomer molecules called amino acids. Each amino acid has a standard backbone atom structure of $N - C_\alpha - C$ (see Figure 1). These amino acids vary based on their distinctive side chains, resulting in 20 different types. When hundreds to thousands of amino acids chain together through peptide bonds, they create proteins. The sequence of amino acids dictates the protein's final 3D structure. The structure of a protein, in turn, determines the biological activity and function of the protein.

The design of proteins is driven by their vital role in the functioning of living organisms. This task is motivated by the potential to optimise the functionality of proteins or create new ones. Given the pivotal role of proteins in living organisms, a crucial need for designing proteins arises, whether to enhance their activities or to create new ones. These engineered proteins might unlock opportunities for uncovering innovative methods to leverage cellular pathways. Potentially paving the way for novel treatments aimed at currently untreatable diseases [Koutsopoulos 2017] or for their use in biochemical applications in various industrial settings[Leiman and Taylor 2019].

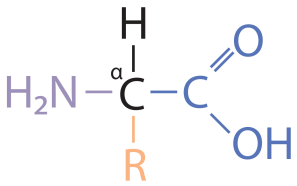

Figure 1: The molecular structure of an amino acid in its un-ionised form. Showing the central alpha carbon (black), the carboxyl group (blue), the amino group (purple), and the variable side chain (yellow)

Unfortunately, the design of proteins faces a major hurdle due to the enormity of the protein search space, which could encompass potentially 20^{100} amino acid sequences for a 100 residue protein. Moreover, natural evolution has only explored a limited size of this expansive space [Dryden et al. 2008]. Consequently, there is a broad unexplored design landscape with the potential to reveal entirely new proteins possessing novel properties and functions. However, the sheer size of this design space, coupled with the costs involved in experimental validation [Jaskolski et al. 2014], results in significant challenges in developing effective tools for designing *de novo* protein sequences with specific desired structures and features [Paladino et al. 2017].

Historically, protein design required minimal and rational design approaches whereby the placement of each residue in a design was reasoned using chemical principles and/or biochemical knowledge[Woolfson 2021]. This reliance on labour-intensive experimental techniques required significant expertise. The advent of computational methods and machine learning facilitated a more efficient exploration of the protein search space, enabling the utilisation of these innovative approaches. In recent times, generative models, a subset of deep learning models capable of producing novel outputs following a specified distribution, have captured the attention of protein researchers.

Various generative models have had significant successes in various fields, each offering unique capabilities and applications. Deep Generative Adversarial Networks (GANs), as pioneered by [Goodfellow et al. 2014], involve a dual learning process where two models compete against each other: a generator for crafting novel instances and a discriminator for categorising them as real or fake. However, one drawback of GANs is that they tend to lack diversity in their output. On the other hand, Variational autoencoders (VAEs), as proposed by [Kingma and Welling 2013], employ an encoder-decoder setup that facilitates easy sampling from the latent space, resulting in more diverse output. Although VAEs can produce more

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diverse outputs, they often lack quality. Diffusion models, which have gained prominence recently, address these limitations.

Diffusion models were pioneered by [Sohl-Dickstein et al. 2015] [Ho et al. 2020] [Dhariwal and Nichol 2021]. In recent years significant advancements have been made, mainly in the field of computer vision, resulting in state-of-the-art solutions [Nichol et al. 2021] [Rombach et al. 2022] [Ruiz et al. 2023]. These models possess a set of features that is highly relevant for the generation of novel proteins [Watson et al. 2023]. That is, diffusion models exhibit the ability to generate diverse outputs that can be conditionally guided toward specific design objectives, which is not as easily done in other generative models. Furthermore, they possess the capability of inpainting, allowing them to fill in missing portions of partially complete inputs. Lastly, diffusion models offer rotation-equivariant output by employing specialised equivariant architectures.

One recent major advancement in the field of protein analysis and design is the AlphaFold2 model by Goolge's Deepmind [Jumper et al. 2021]. AlphaFold2 achieved experimental-level accuracy for protein structure prediction, which revolutionised the field. Following its success subsequent models such as RoseTTAFold [Baek et al. 2021], ESMFold [Lin et al. 2023], HelixFold-Single [Fang et al. 2023] and OmegaFold [Wu et al. 2022] have either replicated or approached similar levels of performance.

Although these methods excel at modelling static experimental structures derived from crystallography or cryo-electron microscopy (Cryo-EM) data, proteins in their natural environments are not static and exhibit dynamic structural ensembles. This dynamic behaviour is caused by interactions with the environment and causes the protein's structure and function to change. These changes can initiate various important reactions that help control biological functions. The distributional modelling properties of diffusion models can help to find the dynamic structure of proteins.

The generation of proteins involves creating new protein sequences or structures. There are two primary types of protein generation, either by optimising existing proteins or by creating novel proteins. Optimising existing proteins involves refining or modifying existing proteins to improve certain properties, such as binding affinity. The creation of novel proteins requires the design of entirely new proteins. The generation of proteins can involve the generation of desired sequences or structures either partial or complete. Sequence and structure co-design involves generating sequences and structures jointly.

Previous surveys have explored the application of diffusion models in bioinformatics [Guo et al. 2023] and other deep learning methods in protein design [Bennett 2023] [Kim et al. 2023]. A recent survey explored the use of graph diffusion models in molecular, protein, and material design[Zhang et al. 2023]. This survey uniquely focuses on the use of conditional generation within diffusion models for protein design.

Conditioning, within the scope of this survey on protein design, refers to the deliberate introduction of additional protein property information to guide the generative part of the diffusion process toward a specific, intended outcome. In this context, the protein property information significantly shapes the desired result. Rather than randomly selecting a protein from the overall learnt distribution, conditioning ensures that the sample originates from a smaller intended subset within the total distribution. This conditioning information encompasses various protein properties, such as the protein's desired (partial) structures, sequences, or other relevant biophysical attributes. This can also be characteristic information about the (partial) structure or sequences of a binding molecule. Therefore, conditioning is a crucial element of protein design, as it allows designers to tailor protein properties to meet specific objectives.

To illustrate the specific application of this concept, let us consider the following example within a defined context. In protein design, using a structural graph representation of a binding ligand means incorporating specific atom arrangements and bond details crucial for targeting a receptor. For instance, creating a protein for targeted therapy involves ensuring its structure aligns with the depicted ligand graph, enabling precise binding to a specific receptor, like those found on cancer cells, thus enhancing its therapeutic potential.

This survey begins by providing background on the foundational concepts of diffusion models and how they are used in the context of protein design in Section 2. Subsequently, we explore various conditional settings in Section 3, Section 4, Section 5 and Section 6. For a hierarchical overview of the discussed conditional settings in this survey see Figure 2. A brief overview of the unconditional sampling of the discussed research can be found in Section 7. Then in Section 8 a discussion as well as future directions for the field of protein design are highlighted. Finally, we conclude this survey in Section 9.

2 BACKGROUND

2.1 Diffusion models

Diffusion models try to learn a data distribution by slowly adding noise to its input and then trying to systematically remove that noise. These models can utilise various architectures tailored to their specific requirements, adapting the approach of noise addition and removal for optimal performance. By understanding the process of removing the noise, the model can generate novel outputs of the data distribution.

Three subtypes exist within this category: Denoising Diffusion Probabilistic Models (DDPMs) [Sohl-Dickstein et al. 2015], Score-based Generative Models (SGMs) [Song and Ermon 2019], and Stochastic Differential Equations (SDEs) [Song et al. 2020]. These subtypes vary in their approaches to executing both the forward and backward diffusion passes. In this section, we will only discuss the DDPMs and SDEs since only these models are used in the research discussed in this paper. An overview of DDPMs and SDEs can be found in Figure 3.

2.1.1 Denoising Diffusion Probabilistic Models(DDPM). A Denoising Diffusion Probabilistic Model (DDPM) is a type of generative model capable of creating new *discrete* data samples from a specified data distribution, using a dual Markov chain approach.

In the DDPM framework, the first stage involves the forward diffusion process, which iteratively transforms the original distribution across a specified number of steps, denoted as T. This transformation gradually introduces noise, ultimately converging toward a simpler prior distribution, often a Gaussian distribution.

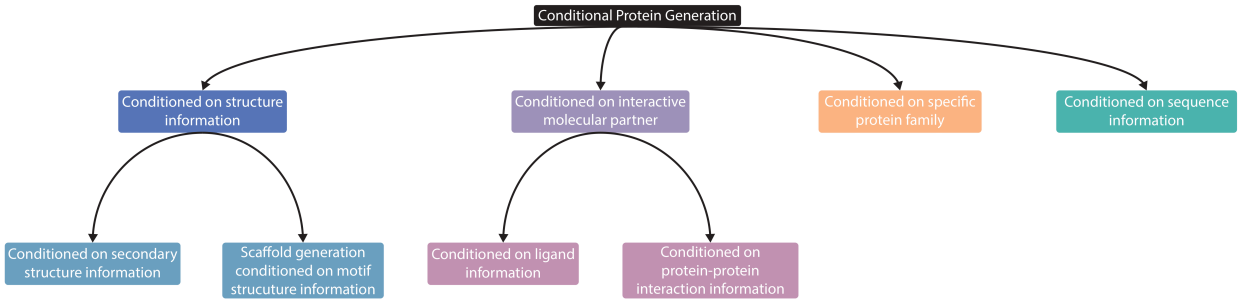

Figure 2: Hierarchical overview of the various conditional settings that are discussed in this survey.

The reason for transforming to such a distribution is that this distribution can be used for easy sampling later. Notably, the amount of noise added at each step is controlled by a predefined variance schedule denoted as β. Formally, the forward process is defined by the posterior probability $q(x_t|x_{t-1})$, where x_t signifies the original input with noise corresponding to the time step t. The full forward process can be defined as follows:

$$q\left(x_{1:T} \mid x_0\right) = \prod_{t=1}^{T} q\left(x_t \mid x_{t-1}\right), \tag{1}$$

$$q\left(x_t \mid x_{t-1}\right) = \mathcal{N}\left(x_t; \sqrt{1-\beta_t} x_{t-1}, \beta_t I\right) \tag{2}$$

Where $\beta_t \in [0,1]$ is linked to the variance schedule. Using $\alpha_t = 1 - \beta_t$ and $\bar{\alpha_t} = \prod_{s=1}^{t} \alpha_s$ we can rewrite the previous equation to:

$$q(x_t|x_0) = \mathcal{N}\left(x_t; \sqrt{\bar{\alpha}_t} x_0, \left(1-\bar{\alpha}_t\right) I\right) \tag{3}$$

Lastly, the backward diffusion process uses a neural network architecture θ that learns to predict the noise that was added in a forward step. This backward process is designed to reconstruct the original input based on the predicted noise at each time step. The backward process is formally given as $p_\theta(x_{t-1}|x_t)$, and the optimisation of the model is guided by the following objective.

$$p(x_{t-1}|x_t) = \mathcal{N}(x_{t-1}; \mu_\theta(x_t, t), \Sigma_\theta(x_t, t)) \tag{4}$$

Where $\mu_\theta(x_t, t)$ and $\Sigma_\theta(x_t, t)$ predict the mean and the variance of the noise at time t respectively. In practice, the variance is often kept fixed and only the mean is predicted. The works by [Ho et al. 2020] gave us a simplified version of the objective denoted below:

$$L_{\text{simple}}(\theta) := \mathbb{E}_{t,\mathbf{x}_0,\epsilon}\left[\left\|\epsilon - \epsilon_\theta\left(\sqrt{\bar{\alpha}_t}\mathbf{x}_0 + \sqrt{1-\bar{\alpha}_t}\epsilon, t\right)\right\|^2\right] \tag{5}$$

2.1.2 Stochastic Differential Equations (SDEs). Stochastic Differential Equations (SDEs) are a class of mathematical models that illustrate how a system evolves amidst random noise. In the research carried out by [Song et al. 2020], the authors revealed the connection between SDEs, SGMs and DDPMs which lies in their fundamental principles. SDEs, as a framework, support the dynamics of probabilistic modelling in both SGMs and DDPMs, allowing the generation of data by specifying the evolution of probability distributions over time via stochastic processes, forming the basis for these generative models. While SDEs naturally handle *continuous* data due to their continuous-time nature, DDPMs discretise these continuous-time models, adapting the framework to generate *discrete* data sequences.

A Score-based Stochastic Differential Equation (Score SDE) is a type of SDE where the drift term is defined as the negative gradient of a score function, and the diffusion term is a function of time as defined by [Song et al. 2020]. A score function $\nabla_x \log(p(x))$ represents the gradient of the log probability density function to the data x.

A forward Stochastic Differential Equation (SDE) is a mathematical framework that shows how a variable changes over time, considering both predictable and random factors in a continuous-time setting. It is characterised as follows:

$$dx = f(x,t)dt + g(t)dw \tag{6}$$

A reverse Stochastic Differential Equation (SDE) describes a continuous-time system that operates in a backward manner, often used to compute the score function for the forward SDE. This score function is utilised to generate samples from the conditional distribution. The reverse SDE is typically defined as follows.

$$\mathrm{d}x = \left[f(x,t) - g^2(t)\nabla_x \log p_t(x)\right]\mathrm{d}t + g(t)\mathrm{d}\bar{w} \tag{7}$$

The score function is approximated by parameterisation in a score model, denoted as $s_\theta(xt, t)$. This process extends the goal of scoring matching to continuous time, as specified by [Yang et al. 2023].

$$\mathbb{E}_{t\sim\mathcal{U}[0,T]),\mathbf{x}_t\sim q(\mathbf{x}_t|\mathbf{x}_0)}\left[\lambda(t)\left\|s_\theta\left(\mathbf{x}_t, t\right) - \nabla_{x_t}\log q_{0t}\left(\mathbf{x}_t \mid \mathbf{x}_0\right)\right\|^2\right] \tag{8}$$

2.1.3 Incorporating Conditional Information. To generate samples that exhibit specific characteristics or conform to particular conditions, these models often incorporate conditional information to influence the generation process. Importantly, the forward diffusion process only adds noise to data so it is irrelevant to data or contexts but the generative diffusion process depends on the given condition and full observation of the previous step. This conditioning can be applied in various ways, allowing the generation of samples to adhere to specific criteria or constraints.

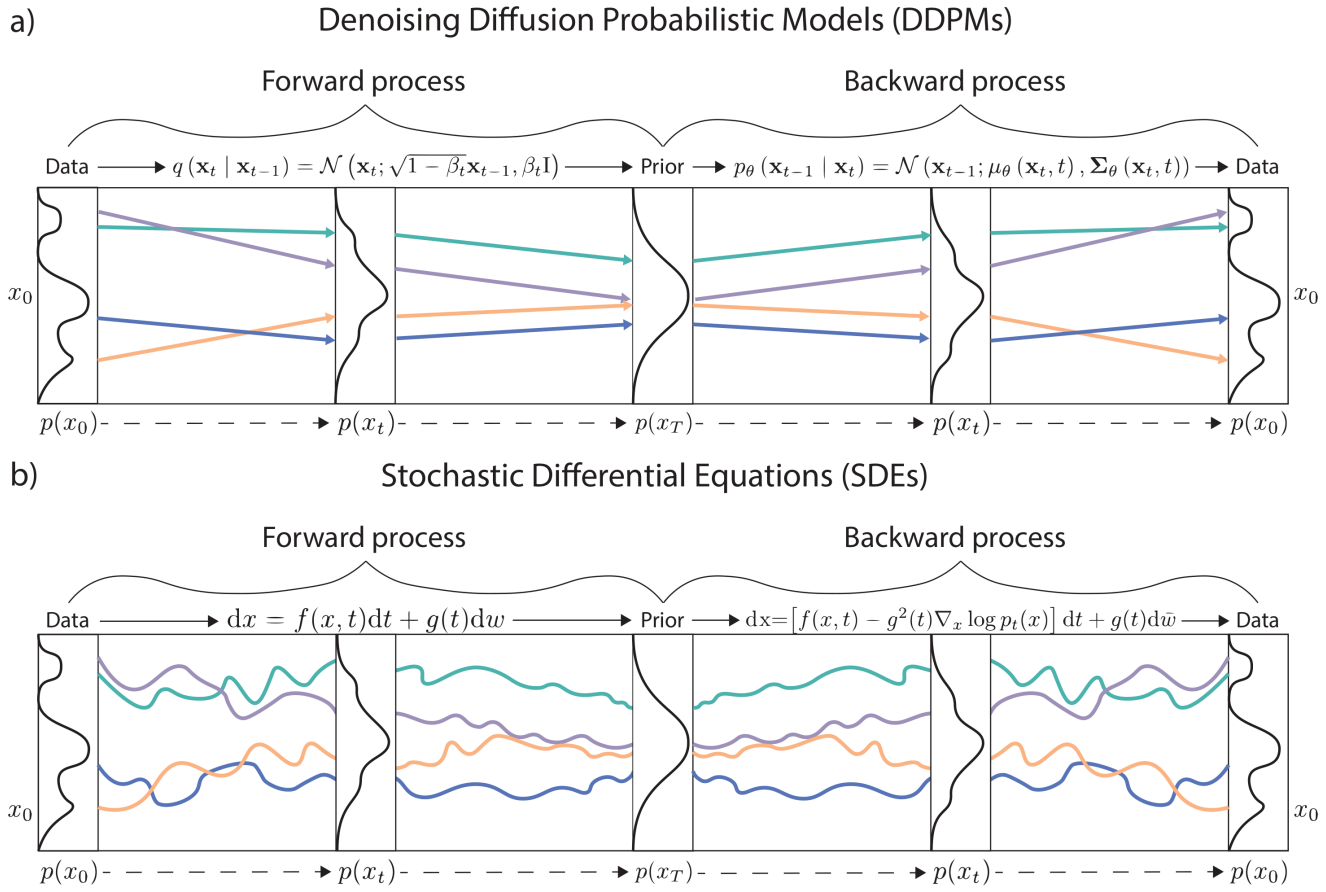

Figure 3: Overview of DDPMs (a) and SDEs (b). A forward process can map our complex data distribution to a noise distribution (the prior). The backward process reverses this noising for generative modelling. During these processes use DDPMs (a) discrete steps and SDEs continuous steps.

One method involves utilising conditional distributions, such as $p(x_t \mid y)$, where x_t represents the sample at time step t, and y denotes the conditioning information. This approach enables the model to generate samples based on given conditional data, like class labels, attributes, or any other relevant information. This conditional distribution can be modelled using a separate classifier, heuristic or some other approximation.

Furthermore, these models can be guided by using a wide array of input data, ranging from simple labels or attributes to more complex structured data. This guidance assists the model in learning and generating samples that align with the provided conditions, making the generated outputs more controllable and tailored to specific requirements. These input data are often embedded and applied using some attention-based module [Vaswani et al. 2017].

In summary, DDPM and SDE are distinct generative modelling techniques with different underlying principles and applications. DDPM focuses on auto-regressive modelling and discrete data, while SDE models the continuous dynamics of data and is more versatile in terms of data types. The choice between them depends on the specific problem and the nature of the data with which one is working.

2.2 Datasets, Post-Processing and Validation

Dataset selection, post-processing and validation of proteins play a crucial role in the accurate generation and analysis of conditional protein structures using diffusion models.

2.2.1 Protein Data Bank. The Protein Data Bank [Berman et al. 2000] serves as a primary source of protein structures. Several specific subsets of this database can be used for their design-specific tasks, such as SAbDab which encompasses antibodies or CATH which provides a hierarchical classification of protein domains based on their folding patterns. Since a diffusion model can use different architectures, the used data must match the selected architecture and vice versa.

2.2.2 Post-Processing. The generated proteins often are not specified as full-atom proteins. Several techniques can be utilised to refine and complete the generated protein fully. Protein structure refinement and enhancement can be done using post-processing methods such as ADMM (Alternating Direction Method of Multipliers) [Boyd et al. 2011] and Rosetta [DiMaio et al. 2009]. Additionally, side chain packing algorithms [Alford et al. 2017] can be used to determine the correct placement of side chains and obtain reliable and realistic protein conformations.

2.2.3 Validation. Various techniques validate generated proteins. In silico validation involves a range of computational assessments, such as sequence novelty analysis using BLAST[Altschul et al. 1990], energy calculations, structural analysis using Root-Mean-Square Deviation (RSMD), and advanced structure prediction techniques like AlphaFold [Jumper et al. 2021]. These methods collectively assess and confirm the stability, reliability, and accuracy of the protein structures generated. Additionally, in vitro validation involves experimental methods such as biophysical techniques in a lab (e.g., X-ray crystallography, NMR spectroscopy, cryo-EM) to experimentally validate protein structures, along with functional evaluation to confirm protein function and properties.

2.3 Nomenclature

A table comprising common abbreviations and acronyms relevant to conditional protein design via diffusion models can be seen in Table 2. This table serves as a quick reference guide, offering an inventory of frequently used terms and acronyms within this article.

Table 1: Nomenclature table.

DDPM	Denoising Diffusion Probabilistic Model
SDE	Stochastic Differential Equation
SGM	Score-based Generative Models
HDM	Harmonic Diffusion Model [Jing et al. 2023]
EGNN	Equivariant Graph Neural Network
ETNN	Equivariant Transformer Neural Network
MLP	Multi-Layer Perceptron
ECNN	Equivariant Convolutional Neural Network
PLM	Protein Language Model
APMixer	Aligned Protein Mixer [Martinkus et al. 2023]
RMSD	Root-Mean-Square Deviation
CDR	Complementarity-determining Regions
BLAST	Basic Local Alignment Search Tool

3 PROTEIN DESIGN THROUGH CONDITIONING ON ITS STRUCTURE PROPERTIES

The structure of a protein is classified into four levels: the primary structure, which denotes the amino acid sequence without 3D considerations; the secondary structure, defining localised folding patterns or motifs such as alpha helices and beta-pleated sheets over several dozen amino acids; the tertiary structure, describing the intricately folded state of the entire amino acid chain; and, in cases where proteins consist of multiple amino acid sequences, the quaternary structure, determined by the arrangement of these chains.

Conditioning protein design on motifs or secondary structures offers several advantages. One benefit is the influence of secondary structure information on the mechanical properties of protein materials, making it advantageous to use specific information for the design of proteins with desired mechanical characteristics. Another advantage lies in the flexibility of this approach, as it avoids excessively restricting the model to generate only one structure, allowing considerable variation while adhering to specified secondary structure constraints.

The following subsections will explore the use of diffusion models to generate protein designs conditioned on various structural information. A brief overview can be found in Table 2 or in the Appendix in Table 3.

3.1 Novel protein generation conditioned on secondary structure information

[Anand and Achim 2022] introduced an equivariant DDPM for generating protein structure backbones based on topological structure constraints embedded and incorporated using Invariant Point Attention (IPA) [Jumper et al. 2021] modules. On top of these generated backbones, they can diffuse the protein's sequence and rotamers, which specify the orientation of a side chain. This allows them to generate full-atom proteins which do not need a post-processing step, making their model completely end-to-end. Their obtained results show that their model can successfully do region recovery or optimisation using inpainting as well as generating novel protein designs. Furthermore, the model also has comparable results when generating sequences and rotamers with baseline models. Since their model can only generate these sequences and rotamers from previously generated backbones, the model is not able to co-design a complete protein, impacting the model's qualitative results by constraining structure, sequence, and rotamers separately

The work by [Ni et al. 2023] utilises a DDPM to create new protein sequences based on secondary structure data, bypassing the atomic backbone construction to concentrate on the correlation between secondary structures and sequences. Their model generates sequences by conditioning on a fractional distribution over 8 different types of secondary structures that are embedded and used using cross-attention. It can also take in more specific conditional information in the form of per-residue secondary-structure information, which is encoded and then concatenated to the input. Post-generation, folding prediction methods are employed to forecast complete protein structures and classify their secondary structures, showing alignment with the conditioning information. Lastly, their generated proteins are validated on novelty via BLAST analysis, which highlights the effectiveness of using the per-residue information in generating de novo sequences with $50\% - 60\%$ similarity. Notable, from their work is that there is no mention of equivariant modelling which is a necessary aspect when designing proteins.

A novel multi-purpose model, called RFDiffusion, was recently proposed by [Watson et al. 2023]. Their model harnesses the success of the structure prediction models by fine-tuning it on protein structure denoising tasks. Specifically, the authors used RosettaFold [Baek et al. 2021], but in theory, any of such structure prediction models could work. The model represents C_α coordinates and $N - C_\alpha - C$ rigid orientation of each residue using the RFframe representation. RFDiffusion is capable of protein generation on several conditioning tasks. RFDiffusion stands out for its ability to generate symmetric oligomers conditioned on specified point group symmetries. These structure symmetry specifications are used as a heuristic during the backward diffusion process. RFDiffusion exhibits high success rates in both in silico predictions and in experimental validation.

Table 2: Tabulated summary of reviewed papers. The initial column displays the contributing authors. The next column highlights the Diffusion types, see Table 1 for context. The third column specifies the architecture utilised in the backward diffusion process; see Table 1 for context. The column of generative type distinguishes between de novo protein generation, optimisation of existing proteins, or generation of dynamic structures. Following that, the Table indicates the various conditioning types used, including structure (CoStr), sequence (CoSeq), interactive molecular partner (CoIMP) or protein family (CoPF). The final column denotes whether the model primarily predicts sequences, predicts structures or applies a co-design approach.

Authors	Diffusion Type	Architecture	Generative type	Conditioning type	Generates	Code available
[Ni et al. 2023]	DDPM	UNET	De novo	CoStr	Sequence	yes
[Trippe et al. 2022]	DDPM	EGNN	De novo and optimisation	CoStr	Structure	yes
[Anand and Achim 2022]	DDPM	ETNN	De novo and optimisation	CoStr	Structure	no
[Jing et al. 2023]	HDM	EGNN	Dynamic structure generation	CoSeq	Structure	yes
[Qiao et al. 2022]	SDE	EGNN	Dynamic structure generation	CoSeq, CoIMP	Structure	no
[Nakata et al. 2023]	DDPM	EGNN	Dynamic structure generation	CoSeq, CoIMP	Structure	yes
[Martinkus et al. 2023]	DDPM	APMixer	De novo	CoPF	Co-design	yes
[Luo et al. 2022]	DDPM	MLP	De novo and optimisation	CoIMP	Co-design	no
[Ketata et al. 2023]	SDE	ECNN	Dynamic structure generation	CoIMP	Structure	yes
[Watson et al. 2023]	DDPM	RoseTTAFold	De novo and optimisation	CoStr, CoIMP	Structure	yes

While this area has seen outstanding results in both the recovery, optimisation and generation of novel proteins by [Anand and Achim 2022], [Ni et al. 2023] and [Watson et al. 2023] it does lack a comprehensive model which can co-design both structure, sequence and rotamers.

3.2 Protein scaffold structure generation conditioned on motif structure

In protein design, scaffolds serve as a stable framework that supports the structural integrity of a specific motif, where motifs are functional protein fragments that contribute to biological functions within the stable structure of the scaffold.

To this end, [Trippe et al. 2022] proposed a two-fold solution. First, they introduced ProtDiff, an unconditional equivariant diffusion model for protein structure sampling. Second, they developed SMCDiff, which uses sequential Monte Carlo (SMC) sampling in tandem with ProtDiff to conditionally sample scaffolds based on a given motif. During the denoising stage, the authors used an approximation method to estimate the conditional probability of a scaffold given a motif. From their limited results, they could conclude that their two-fold solution is the first one capable of generating diverse scaffolds of more than 20 residues with a significantly lower computation time than other previous methods. Notably, they acknowledge the limitation of training and evaluating their model based on the available data, recognising as well the absence of a standard evaluation benchmark for the motif-scaffold protein problem.

The RFDiffusion model [Watson et al. 2023] later reached outstanding results on various motif scaffolding tasks. During training, the conditional probability of a scaffold given a motif is learnt and used during denoising. For functional-motif scaffolding, they proposed a benchmark on which RFDiffusion had an almost perfect score as well as a 21% higher score than the next best model. When their model was tested on scaffolding enzyme active sites, it showed that it was able to scaffold enzyme active sites with high success rates across a range of enzyme classes. Lastly, the model's capabilities were tested on symmetric functional-motif scaffolding, where the scaffold is symmetric, for which it showed in its four test cases that it could design these symmetric scaffolds.

The shortcomings in the lack of data and benchmarks that [Trippe et al. 2022] uncovered during their research was met by [Watson et al. 2023]. While the RFDiffusion model had significant results for various scaffold problems, the model was only tested on four test cases for the symmetric scaffold problem. The model's ability on this problem could be further explored on a larger group of test cases

4 PROTEIN DESIGN CONDITIONED ON INTERACTIVE MOLECULAR PARTNERS

Designing proteins with a focus on their interactions with various molecules, such as ligands, antigens, and other proteins, is of significance in the fields of molecular biology and biotechnology. Protein functionality often relies on specific interactions with other molecules. Understanding and harnessing these interactions is crucial for the development of novel therapeutics and biotechnological applications. An example of how the structure of a protein can change when bound to a ligand can be seen in Figure 4. A compact list of the papers discussed in this section can be found in Table 2 or in the Appendix in Table 3.

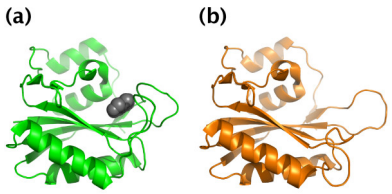

Figure 4: Example of a protein-ligand structure pair between ligand-bound (a) and unbound (b) states [Morita et al. 2011].

4.1 Protein structure generation conditioned on ligand information

In a diffusion setting, the works by [Qiao et al. 2022] were the first to cast the problem of sampling a protein structure given a ligand structure. A ligand is a molecule, often a small chemical compound, that binds to the active site of a protein, modulating the protein's function or activity. NeuralPlexer uses attention modules together with the conditional information to aid the denoising stage. This

information includes the protein sequence, structural information obtained from a protein language model (PML) and the ligand graph representation. The NeuralPlexer method, when applied to binding site structure recovery, showcased a notable success rate in predicting accurate binding pocket structures within a defined radius around the ligand atom coordinates.

The research of [Nakata et al. 2023] modelled the protein-ligand interaction using an EGNN to generate protein structures conditioned on the protein sequence and the graph representation of the target ligand. During each denoising step, conditional information is embedded and appended to the noise input. Additionally, they generate proteins without protein structural information, unlike NeuralPlexer, and from their results they showcased that this still results in properly generated structures. They then compared their model against other molecular docking methods and showed that their model had comparable or better results than these models. The model seems especially effective compared to other models when dealing with ligands of larger size.

The authors from the RFDiffusion model [Watson et al. 2023] fine-tuned their model to design binders for target molecules, both with and without conditioning on compatible fold information. Conditioning information in this setting is used during denoising as the gradient of a heuristic rather than using a trained classifier. The greatest contribution of their results is that high-affinity binders can be identified from dozens of designs instead of several thousand for previous models.

Current research thus far has solely focused on designing proteins which are in their bound state with a ligand. Since proteins have different conformations depending on their bound state, research should also focus on designing proteins in both their bound and unbound state. This will aid when expressing and validating such proteins experimentally in a lab.

Other notable research, such as DiffDock [Corso et al. 2022] and DiffBP [Lin et al. 2022], has also employed diffusion-based techniques to explore protein-ligand interactions. However, it is essential to note that these methods primarily concentrate on generating potential ligand poses for given ligand-protein pairs and do not directly address protein design. Consequently, they fall outside the scope of this study.

4.2 Conditionally generating protein-protein interaction structures

[Ketata et al. 2023] were inspired by the DiffDock model and focused on rigid protein-protein docking using the DiffDock model. In their work, they generate binding protein poses while keeping the receptor protein fixed. Notable is that they only consider protein structures in their rigid bounded state and keep internal bonds, angles and torsion angles fixed during generation. When only generating one sample, their model outperforms the majority of the baseline models. Since its model is generative of nature, it generates a distribution of possible protein-protein complexes. When they select the complex with the smallest RMSD from their generated samples, DiffDock-PP performance exceeds that of all baseline models by a large margin. The authors mention that due to time constraints, they were unable to evaluate DiffDock-PP on the Docking Benchmark 5.5 (DB5.5) dataset, which could lead to different model results. Additionally, from their paper, it is unclear how the conditioning information is provided to the diffusion model.

Another form of protein-protein interaction is the interaction between antibodies and antigens. Antibodies are specialised proteins created by the immune system and designed to bind to specific foreign entities called antigens. These proteins contain specialised regions called complementarity-determining regions (CDRs) that bind to particular parts of antigens, allowing the immune system to identify, neutralise, or mark them for removal. The strategic design of CDRs is necessary for crafting medical antibodies tailored to target known antigens.

One diffusion-based approach that stands out in the design of these CDRs is [Luo et al. 2022]. Their model, called DiffAb, is explicitly conditional on the protein complex, consisting of an antigen and an antibody framework, allowing it to be generalised to new antigens. The model jointly diffuses the three components of a protein, namely the amino acid types, the C_α coordinates and the amino acid orientations, allowing for co-design of the full protein. DiffAb directly learns the conditional distributions, since conditioning is included in the objective function. The model is tested in CDR inpainting on three antibodies and compared with other models. When testing the model's ability to recover and co-design recover CDRs, it has competitive results. It also shows that their model has reasonably good binding energy on the Rosetta validation method without explicitly being learnt on this validation method, unlike other models. Additionally, in addition to CDR recovery, DiffAb is also able to optimise an antibody binding energy.

The DiffDock model generates high-quality protein poses but thus far only considers protein-protein interaction in their bound state. Further research could investigate the design of both bound and unbound states. The DiffAb only generates CDRs but does not consider the generation of full antibodies given an antigen, warranting further research.

5 PROTEIN DESIGN CONDITIONED ON SPECIFIC PROTEIN FAMILIES

Motivated by the observation that key large protein families, typically have strong properties, such as being able to be mapped to a reliable sequence ordinate via sequence alignment, AbDiffuser was developed [Martinkus et al. 2023]. A high-level overview of the AbDiffuser model can be found in Table 2 or in Table 3. The conditioning is done by incorporating family-specific priors during the diffusion process. Their solution incorporates priors from the antibody family and consequently generates antibodies. Their approach differs from existing antibody design methods since AbDiffuser extends beyond CDR generation to encompass the full antibody structure. Claiming that generating complete antibodies broadens design possibilities, such as optimising stability or immunogenicity, and potentially impacting antigen interaction and CDR conformation. The results show that AbDiffuser demonstrates robust antibody generation with lower memory requirements than previous models, despite having more model parameters. Furthermore, from their in-vitro wet lab experiments, they can conclude that their generated antibodies have a higher binding affinity than previous models while using significantly fewer samples. Lastly,

they state that their model can also generalise to other large protein families but this warrants further research.

6 PROTEIN STRUCTURE DISTRIBUTION GENERATION CONDITIONED ON SEQUENCE

This section will delve into how diffusion models' distributional modelling properties have been researched to help determine the dynamic structure of a protein conditioned on its sequence. A compact list of the papers discussed in this section can again be found in Table 2 or in the Appendix in Table 3..

The novel model, NeuralPlexer [Qiao et al. 2022], was first proposed to generate protein structure distributions. Specifically, it was tested on ligand-binding proteins that exhibit large conformational variability and the results show that NeuralPlexer gives the highest performance compared to the best-performing structure prediction methods. These other best-performing methods do not take into account crucial ligand information. This shows from their results that this additional conditional ligand information is necessary when predicting the structure of ligand-binding proteins.

Another diffusion-based model that generates dynamic protein-ligand structures conditioned on the sequence was developed by [Nakata et al. 2023]. The outcomes produced by their model showcased a variety of structures, with accurate protein conformations and binding positions for ligands. Although giving good results, this model has been limited by producing proteins of limited size and a lack of training data.

Lastly, there is Eigenfold [Jing et al. 2023], which uses a novel diffusion process called harmonic diffusion and eigenmodes to generate dynamic protein structures from a fixed protein sequence. From their research, it is still unclear how the sequence information is incorporated into their method. When testing their model for single-structure prediction, it is only comparable to RoseTTAFold [Baek et al. 2021] but still inferior to AlphaFold2[Jumper et al. 2021] and ESMFold [Lin et al. 2023]. The results from tests on conformational diversity show that Eigenfold is lacking as well, being unable to generate highly accurate protein models that effectively represent the full range and specific details of protein conformational changes, thereby showing limitations in accurately capturing the diverse structural variations.

The Eigenfold model did not bring better results than traditional SOTA models in this area. Since the research from [Qiao et al. 2022] and [Nakata et al. 2023] showed that in a specific conditional setting, they could generate better results than the traditional models, it could be interesting to see if altering these models for different conditional settings could harbour the same good results.

7 UNCONDITIONAL PROTEIN SAMPLING

Some of the models previously discussed also allow for unconditional protein sampling. In this section, we will briefly highlight these results.

The unconditional model ProtDiff [Trippe et al. 2022] is evaluated on the agreement of their backbone sample with the AlphaFold2 predicted structures. From their results, they show that most protein designs, especially proteins of longer sequence size are designs which are not novel. This observation raises questions about the diversity and originality of the conditional protein designs generated through unconditional means.

The RFDiffusion model [Watson et al. 2023] can readily generate diverse unconditional designs of up to 600 residues in length. These designs are validated in that they are accurately predicted by AlphaFold2, far exceeding the complexity and accuracy achieved by most previous methods. This achievement shows that diffusion models generating proteins without conditioning can design long and accurate protein structures.

8 DISCUSSION AND FUTURE WORK

Recognizing the dynamic nature of the field, this survey provides a focused snapshot rather than a comprehensive overview due to the vastness of protein design and the constant influx of new research. Time constraints also limit the scope of this survey, inevitably omitting certain developments.

Many works in the field of protein design often encounter a lack of quality training data, which emphasises the importance of the generation of viable artificial protein generation. Most current papers tend to train their models on a relatively limited number of proteins, and testing is frequently confined to only a handful of proteins. This scarcity of available viable proteins consequently impedes the development of well-rounded models.

One promising direction for advancing protein design involves establishing a standardised methodology for testing and evaluating protein designs. Given the varied ways in which proteins are validated, authors could selectively choose metrics that favour their models. To address this, it would be beneficial to propose benchmarks tailored to specific design categories. This approach would enable methods to be compared on a level playing field, encouraging healthy competition among researchers and leading to new advancements in the field of protein design, similar to the impact of standardised benchmarks in various other domains of deep learning [Richter et al. 2017]. Moreover, standardizing the representation of proteins, particularly in neural network architectures, would enhance consistency and comparability across different methodologies. Lastly, most research discussed in this survey has publicly available code, which is a good practice which is not always adhered to. The availability of these resources aids in the progress, comparison, validation and reproduction of research and development.

Additionally, most methods discussed in this paper focus solely on generating either protein sequences or structures. For example, a crucial aspect of enzyme design involves identifying the optimal arrangement of side chains around the binding site to stabilise the transition state. Exploring methods that integrate co-design principles and adopt an end-to-end approach, addressing both sequence and structural aspects simultaneously, would produce better proteins and further advance the field of protein design.

One aspect that the current discussed literature lacks is explicit conditioning on biochemical and biophysical properties, such as binding affinity or temperature degradation. These characteristics are useful when utilising proteins in a controlled industrial setting. Optimising certain properties of proteins has cost-saving benefits in these settings.

Most research discussed in this paper has seen only success in generating proteins of shorter length, in the order of tens to hundreds of amino acids. Since proteins can be thousands of amino acid residues long, further research should be done in designing proteins of these lengths.

Since diffusion models are commonly utilised and facilitate the most progress in computer vision it could be of value to take inspiration from the progress in this field [Croitoru et al. 2023]. One example is ControlNet [Zhang and Agrawala 2023], a neural network architecture that adds spatial conditioning controls to large, pre-trained text-to-image diffusion models. This allows the model to use edge maps that need to be in the final output of the model. This spatial conditioning could be beneficial for the structural generation of proteins. Other notable research that could be beneficial has focused on faster sampling techniques [Zhang and Chen 2022] or on different conditional guidance methods [Singh et al. 2022]

Future research in conditional diffusion models for protein design can leverage success from the success these models have had in the field of molecular design. One example is EDM (Energy-Based Diffusion Model) [Hoogeboom et al. 2022], which introduces diverse noise to sample molecular conformations, serving as a foundation for accurate structure generation. Furthermore, DiffSBDD (Structure-Based Drug Design) [Schneuing et al. 2022] employs equivariant DDPM to generate small molecule ligands with high specificity to protein pockets, presenting a powerful tool for crafting high-quality ligands which could be used in collaboration with the design of ligand-binding proteins. Lastly, traditionally diffusion methods have used isotropic Gaussian noise for the forward process. Applications for molecule structure generation have increasingly featured non-isotropic or non-Euclidean processes that exploit the reduced degrees of freedom and chemical priors in a molecular structure, which could warrant further research for protein design as well.

Furthermore, since both molecular design and protein design model the correct placement of atoms, one future direction could be a multi-purpose model which could do both. Such a general-purpose method would streamline the design process by integrating the principles of molecular and protein design, offering a comprehensive tool capable of accommodating diverse atomic structures.

Lastly, access to improved models that inform the development of therapeutics, vaccines, and other applications is undoubtedly advantageous for researchers. However, the presence of such powerful tools for protein design comes with inherent risks. The accelerated progress in computational methods due to AI techniques might pose challenges for the research community to adapt and self-regulate effectively in response to rapid advancements in method capabilities. Additionally, there is a concern that these methods might be exploited for potentially malicious purposes, underscoring the need for responsible and ethical implementation and oversight.

9 CONCLUSION

To conclude, the field of conditional protein design with diffusion models has seen significant advancements in various fields. While most of the discussed methods bring new ideas and improvements to their respective area, there are still improvements to be made. All in all, the potential for these models to revolutionize protein design is promising, with continued exploration and innovation paving the way for more sophisticated and efficient guided applications.

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A ADDITIONAL MATERIALS

Table 3: Extended informational overview of the discussed papers. The first column displays the contributing authors. The column after that gives a small description of how the conditional information is incorporated into the diffusion models. After that, there is a column which shows if the conducted research also considers unconditional sampling. The last column highlights how the results are validated.

Authors	Incorperation of condition information	Unconditional	Validation
Bo Ni et al. (2023)	Attention-based and concatenated to input	-	In silico
Brian Trippe et al. (2023)	Approximation of conditional distribution	Yes	In silico
Namrata Anand et al. (2022)	Attention-based	-	In silico
Bowen Jing et al. (2023)	-	-	In silico
Zhuoran Qiao et al. (2022)	Attention-based	-	In silico
Shuya Nakata et al. (2022)	Concatenated to input	-	In silico
Karolis Martinkus et al. (2023)	Encoded prior information	Yes	In silico & In vitro
Shitong Luo et al. (2022)	Learnt conditional distribution	-	In silico
Mohamed Amine Ketata et al. (2023)	-	-	In silico
Joseph Watson et al. (2022)	Heuristic or learnt conditional distribution	Yes	In silico & In vitro