

Mapping the Inner Workings of the Microbiome: Genomic- and Metagenomic-Based Study of Metabolism and Metabolic Interactions in the Human Microbiome

Ohad Manor,^{1,4} Roie Levy,^{1,4} and Elhanan Borenstein^{1,2,3,*}

¹Department of Genome Sciences

²Department of Computer Science and Engineering
University of Washington, Seattle, WA 98102, USA

³Santa Fe Institute, Santa Fe, NM 87501, USA

⁴Co-first Authors

*Correspondence: elbo@uw.edu

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The human gut microbiome is a major contributor to human metabolism and health, yet the metabolic processes that are carried out by various community members, the way these members interact with each other and with the host, and the impact of such interactions on the overall metabolic machinery of the microbiome have not yet been mapped. Here, we discuss recent efforts to study the metabolic inner workings of this complex ecosystem. We will specifically highlight two interrelated lines of work, the first aiming to deconvolve the microbiome and to characterize the metabolic capacity of various microbiome species and the second aiming to utilize computational modeling to infer and study metabolic interactions between these species.

Introduction

The human microbiome—the collection of microorganisms that colonize the human body—plays an important role in several physiological processes and ultimately in our health (Clemente et al., 2012; White et al., 2011; Zarco et al., 2012). Of the many communities that comprise the microbiome, the one that resides in our gut is especially intertwined with our own physiology and is tightly linked to our metabolism. The metabolic capacities of this gut microbiome allows us, for example, to harvest otherwise inaccessible energy from our diet (Bäckhed et al., 2004; Gill et al., 2006; Thomas et al., 2011; Xu et al., 2003) and to bio-transform various xenobiotics (Clayton et al., 2009; Maurice et al., 2013; Sousa et al., 2008; Ursell and Knight, 2013). To a large extent, the microbiome can therefore be viewed as a human organ, with specific tasks, operation modes, and capacities (Baquero and Nombela, 2012; O'Hara and Shanahan, 2006).

Considering its profound impact on our own metabolism, it is perhaps not surprising that the gut microbiome has been associated with several metabolic diseases including obesity (Ley et al., 2005, 2006; Turnbaugh et al., 2006, 2008; Upadhyay et al., 2012) and type 2 diabetes (Qin et al., 2012). The discovery of such associations and the growing appreciation for the impact that the gut microbiome has on our health have promoted extensive efforts to study the microbiome and to characterize its taxonomic and genetic composition. Much of this effort has been focused on identifying compositional shifts associated with diseases or with specific perturbations (Theriot et al., 2014). Such studies provide crucial clues into the way the microbiome affects our health and contributes to various host phenotypes. To date, however, much less is known about the inner workings of the microbiome and the various metabolic mechanisms that are at play in this ecosystem.

Two major obstacles impede progress in particular: The first concerns the inherently inextricable nature of the microbiome

and of much of the data generated to study it. The gut microbiota of each individual comprises hundreds to thousands of taxa, each encoding a unique collection of enzymatic genes and carrying out a unique set of metabolic reactions. An important prerequisite to any mechanistic understanding of the microbiome is therefore a detailed characterization of the capabilities of each species. Unfortunately, however, a species-level analysis is often challenging in the context of naturally occurring communities, as many community members resist isolation and culturing efforts. In fact, it was observed over a century ago that when plating microbial samples, most species do not grow to form colonies (Winterberg, 1898), and today it is estimated that only ~1% of bacterial taxa are readily cultivable under normal conditions in vitro (Vartoukian et al., 2010). Although the fraction of culturable taxa may be higher in human-associated communities, isolation and culturing challenges may still hinder the study of key community members and of the community as a whole. These challenges, in turn, have rendered shotgun metagenomic sequencing the method of choice for studying the microbiome and for many analyses of its functional capacity. Metagenomic technologies bypass the need to isolate and culture individual species, analyzing genomic material obtained directly from a mixed sample of species and characterizing the aggregated gene content in the community (Schloss and Handelsman, 2005; Tringe et al., 2005). These technologies therefore generate convolved data, reflecting “community-level” capacity rather than species-specific capabilities. Additional meta-omic technologies, such as meta-transcriptomics (Frias-Lopez et al., 2008; Turner et al., 2013; Urich et al., 2008), meta-proteomics (Erickson et al., 2012; Keiblinger et al., 2012; Klaassens et al., 2007; Kolmeder and de Vos, 2014), and meta-metabolomics (Lu et al., 2014; McHardy et al., 2013; Ridaura et al., 2013; Theriot et al., 2014; Weir et al., 2013) have also been introduced, again providing community-level measures of

transcripts, proteins, and metabolites without necessarily relating these measures to specific community members (Segata et al., 2013).

The second challenge stems from the inherent complexity of the microbiome ecosystem. Complexity, especially in biology, is a product not simply of the number of parts a system is composed of, but rather of the complex and often nonlinear way in which these parts interact (Weaver, 1948). Such interactions play an essential part in the microbiome clockwork and span multiple organizational scales. Within each species, the orchestrated interconnected activity of hundreds and often thousands of enzymes, both within the boundaries of a single cell and across different cells from this species population, bestows each species with a complex set of metabolic capabilities. Each species further competes for and exchanges metabolites with other taxa in its vicinity and may modulate its metabolic activity in response to environmental shifts or to the activity of other taxa in the community (Little et al., 2008; Schink, 2002). The microbiome, as a whole, in turn interacts with the host metabolism, immune response, and diet. This extremely complex web of interactions is an essential part of the microbiome's capacity, activity, and dynamics, and it is therefore hard to imagine that a principled understanding of this multilevel and hierarchical complex system could be gained without accounting for such interactions (Borenstein, 2012). Furthermore, the composition of taxa in the microbiome can vary substantially over even short time scales (Dethlefsen and Relman, 2011), and with it the set of genes in the metagenome and the overall functional capacity of the community. Diet, for example, was shown to rapidly induce compositional shifts associated with obesity (David et al., 2014), but microbiota transplants were able to induce and subsequently rescue obesity-like symptoms (Ridaura et al., 2013). This plasticity of the microbiome and the bidirectional interaction between the composition of the microbiome and the state of the host make discerning cause and effect with respect to compositional shifts associated with a disease state an extremely challenging task (Duncan et al., 2008; Jumpertz et al., 2011; Schwiertz et al., 2010).

In this perspective, we will review and discuss recent efforts to address these challenges with an eye toward gaining an improved, systems-level mechanistic understanding of the microbiome. We will specifically describe two complementary lines of work. The first aims to untangle the microbiome and to obtain species-specific characterization of metabolic capacities. We will discuss various approaches to isolate and sequence individual species as well as methods for deconvolving the metagenome. The second line of work aims to model the microbiome's metabolic machinery and to infer metabolic interactions between taxa using various *in silico* metabolic modeling frameworks. Combined, this body of work provides a first peek into the inner workings of the microbiome and lays the foundation for a comprehensive, system-level understanding of its function and dynamics.

Untangling the Microbiome: Inferring the Metabolic Capacity of Community Members From Cells to Genomes to Genes

When studying the metabolic capacity of microbial species, each species is often viewed simply as the collection of meta-

bolic reactions it can catalyze. Attention is then focused on determining which annotated gene families or gene orthology groups (such as those defined by KEGG; Kanehisa et al., 2012) are encoded in its genome, ignoring any other sequence-level information that may be embedded in the genome. Many comparative genomic analyses, as well as metabolic modeling frameworks, use this gene-centered representation as a point of departure. In the context of metabolism-focused microbiome research, this representation provides a simple description of the various players in the ecosystem and their capabilities. It allows, for example, for studying the division of labor between different community members or the potential for competition and syntrophy.

Clearly, the convoluted nature of microbial communities makes such species-specific characterization hard to obtain, calling for the development of methods for untangling mixed communities. Importantly, however, untangling can be performed at multiple levels, ranging from a physical isolation of microbial cells, to an assembly-based sequence-level "isolation", to a gene-centered metagenomic deconvolution (Figure 1). Below, we will briefly discuss such efforts, as well as the strengths and limitations of deconvolving the microbiome at the various levels.

Isolating and Culturing "Unculturable" Community Members

Traditional, culture-based techniques have been the cornerstone of microbiology. Accordingly, the most straightforward way to map the metabolic capacities of a given community member involves the physical isolation of this species from the community and subsequent culturing. The genome of the cultured isolate can then be easily extracted and sequenced, and the various genes it encodes can be called and annotated (Delcher et al., 2007; Hyatt et al., 2010). Importantly, isolation and culturing can further facilitate extensive biochemical and experimental profiling to study the physiology of the cultured isolate and to assign functions to the many unknown enzymes encoded by its genome, augmenting any genomic-based predictions. As discussed above, however, efforts to isolate and culture individual community members under normal conditions often fail, suggesting that more sophisticated experimental techniques are required (Stewart, 2012).

Indeed, several studies have recently introduced improved culturing methods in order to grow such previously uncultivated bacteria. Using various anaerobic culturing methods on a mixture of microbes from the human gut community, one study demonstrated it was possible to recover ~56% of species-level taxa in the sample (Goodman et al., 2011). Diluting the mixed culture further enabled obtaining 1,172 taxonomically defined isolates that in principle could be sequenced and annotated. A different study used an *in vivo* cultivation method followed by plating on anaerobic medium to isolate 31 species from the human oral community, likely representing many unknown species and genera (Sizova et al., 2012).

More recently, several single-cell sequencing techniques have been introduced, bypassing the challenges involved in culturing many bacterial species. In these methods, individual cells are separated from the sample using optical trapping on a microfluidic device or fluorescent-aided cell sorting techniques (Rodríguez et al., 2009) and are subsequently lysed, amplified,

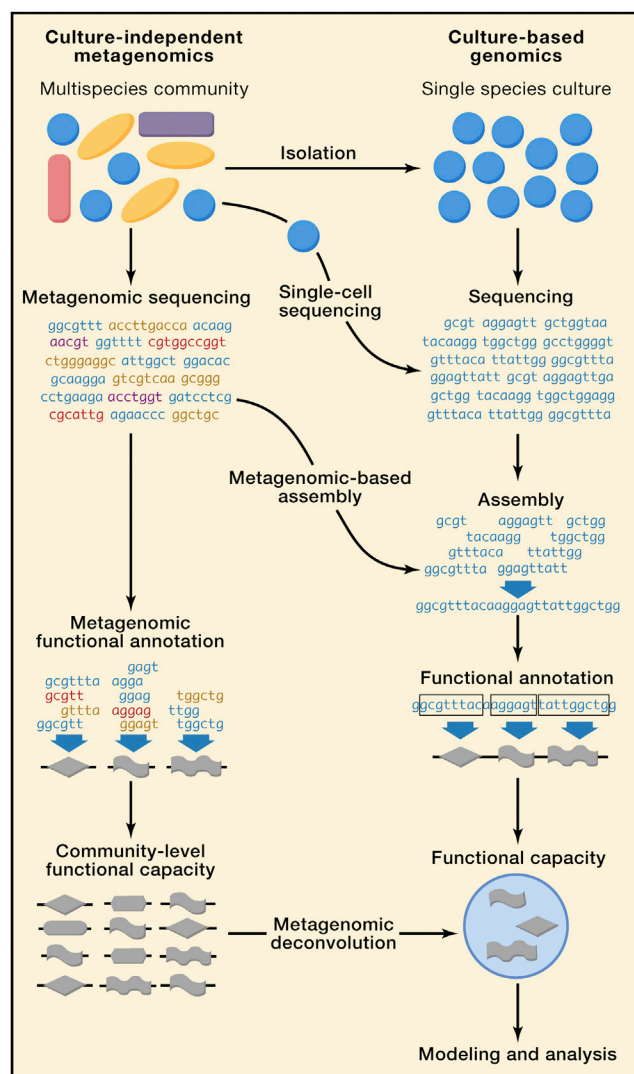


Figure 1. A Culture-Independent Metagenomic Pipeline versus a Culture-Based Genomic Pipeline

Microbiome untangling can be accomplished at several different levels, crossing over from the metagenomic pipeline into the single-species genomic pipeline at various stages, as discussed in the text. Specifically, microbial cells can be physically isolated and cultured or sequenced using single-cell genomics. Shotgun metagenomic short reads can also be assembled de novo into genomes or large contigs using metagenomic-based assembly. Finally, community-level functional profiles can be mathematically deconvolved into species specific functional profiles. Ultimately, the functional capacity of various community members can be characterized, facilitating species-level modeling and analysis.

and sequenced without cultivation. Such an approach was used, for example, to study hot spring sediments and to obtain two nearly complete genomes of a candidate species from a presumed novel bacterial phylum (Dodsworth et al., 2013). Examining the recent oil spill in the Gulf of Mexico, another study has constructed a draft genome of a species from the order *Oceanospirillales* and has examined its metabolic repertoire (Mason et al., 2012). A recent study, aimed directly at sequencing the “dark matter” in the microbial phylogeny, used a similar single-cell approach to isolate and sequence 201 previ-

ously uncultivated bacterial and archaeal strains, uncovering novel metabolic features such as an archaeal-type purine synthesis protein in bacteria (Rinke et al., 2013). Additional efforts to expand and fill in the gaps in the microbial tree of life are currently ongoing (Wu et al., 2009).

Assembly of Genomes from Metagenomes

While the methods described above for isolating, culturing, and ultimately sequencing individual community members are clearly expanding the range of bacterial and archaeal genomes available, some microbial species are still likely to evade isolation efforts. Moreover, such methods are often applied on a small scale and focus on only a single or a few microbial species at a time. A promising alternative therefore avoids isolating an individual species from the community at the physical level altogether, and instead aims to isolate its genome from the metagenome at the sequence level. This “isolated” genome can then be annotated and analyzed to infer the metabolic capabilities of the species.

Various studies, for example, have used standard de novo genome assembly methods (Baker, 2012; Flicek and Birney, 2009) to assemble genomes or large genomic contigs directly from shotgun metagenomic samples (Handley et al., 2014). This approach assumes that reads originating from a given high-coverage genome in the sample will assemble successfully into contigs and thereby separate from other reads. Clearly, however, applying algorithms developed originally for assembling reads from a single-species sample without adjusting them to the complexities of metagenomic data may produce erroneous results. For example, uneven representation of species in the sample could cause genomic regions in highly abundant species to be misidentified as repeats of a single genome (Pop, 2009). Similarly, variations between closely related species in the sample could cause various assemblers to construct distinct contigs for each variant, resulting in a more fragmented assembly (Simmons et al., 2008). Recently, metagenome-specific assemblers have been developed (Beitel et al., 2014; Burton et al., 2014; Iverson et al., 2012; Lai et al., 2012; Laserson et al., 2011; Namiki et al., 2012; Peng et al., 2012; Treangen et al., 2013) that more rigorously address these issues and account for the specifics of metagenomic data. Many such assemblers, for example, aim to first cluster reads or contigs into bins based on nucleotide content, abundance, graph connectivity properties, mate-pair sequences, or spatial proximity and then use these clusters to reconstruct genome scaffolds.

Using such a binning-based approach, several studies have indeed successfully assembled various genomes of interest. In what was perhaps the first attempt to assemble a genome directly from shotgun metagenomic data, GC content was used to partition assembled scaffolds from an acid mine drainage metagenomic sample into bins (Tyson et al., 2004). These bins were then used to construct near-complete genomes of *Leptospirillum* group II and *Ferroplasma* type II. In a study of the surface seawater metagenome, mate-pairing information was used to link assembled contigs into graphs that were then split using nucleotide composition and read-coverage statistics into scaffolds (Iverson et al., 2012). These scaffolds were eventually binned using tetra-nucleotide statistics into several near-complete genomes, including one closed genome representing a previously uncultured marine group II *Euryarchaeota*. In the

context of the human gut microbiome, two studies of the early colonization of the infant gut (Brown et al., 2013; Sharon et al., 2013) binned contigs based on time-series abundance data rather than on nucleotide content, obtaining ~20 complete genomes and studying their predicted metabolic functions, whereas another study combined metagenomic data from the human gut and groundwater to assemble genomes from a new candidate phylum, *Melainabacteria* (Di Rienzi et al., 2013).

Computational Inference of the Genomic Content of Community Members

While metagenomic-based genome assembly methods are likely to expand with the development of long-read and deeper coverage sequencing technologies, they may not be readily applicable in every setting. Even with increased coverage and longer reads, it may be hard, for example, to assemble the genomes of low abundance species, especially in highly diverse communities or when closely related reference genomes are not available. Some computational methods have therefore been introduced, bypassing the assembly process completely and directly predicting the set of genes (or gene families) encoded by a yet-to-be-sequenced species. One such method, termed “metagenomic deconvolution,” specifically aims to decompose metagenomic community-level gene content data (e.g., obtained by mapping shotgun metagenomic reads to known gene families or orthology groups) into taxa-specific gene profiles (Carr et al., 2013). This method relies on the fact that the gene content in a given metagenome is a linear combination of the gene content of the member species and that this relationship can be mathematically modeled when both the taxonomic and the gene content profiles of a given sample are available. Metagenomic deconvolution then uses this model to analyze covariation between the abundances of the various taxa and the abundances of the various gene families across a set of metagenomic samples and identifies the most likely association between genes and their taxa of origin. This approach was shown to successfully reconstruct species-level gene content of microbiome taxa both in simulated data and in samples from the human microbiome project. For a mathematical formulation of the deconvolution framework, see Carr et al., 2013 (and see also Shen-Orr and Gaujoux, 2013 for a general review of deconvolution approaches).

Other computational methods applied different approaches to predict the set of gene families encoded by various yet-to-be-sequenced species. Several such methods, for example, rely on evolutionary gene content conservation, assuming that phylogenetically related species (e.g., those with similar 16S sequences) encode a similar set of genes (Zaneveld et al., 2010). With this assumption in mind, several studies mapped prevalent yet-to-be-sequenced community members to their nearest sequenced reference genome (using 16S similarity), estimating the functional capacity of each of these species (Morgan et al., 2012; Muegge et al., 2011). Taking this approach further, a computational framework has been recently introduced to predict the gene content of organisms that have not yet been sequenced based on the set of genes found in sequenced relatives and on evolutionary modeling (Langille et al., 2013). Specifically, this framework uses a phylogenetic tree and various ancestral state reconstruction methods (Csurös, 2010; Paradis et al., 2004) to infer the gene content of ancestral species and

ultimately the gene content of all species found in a given community. Coupling this inference method with species abundance data, this framework was shown to predict the functional content of the metagenome as a whole.

Modeling Microbiome Metabolism and Metabolic Interactions

Why Model Metabolism?

As discussed above, characterizing the metabolic capacity of each community member is not sufficient to explain the complex inner workings of the microbiome. Rather, the web of interactions between these community members and the way they impact community dynamics need to be mapped in order to gain a fundamental understanding of the microbiome. Such interactions can be probed in various ways. Studying simple synthetic or naturally occurring communities, both in vitro (Kim et al., 2008; Kolenbrander, 2011; McDonald et al., 2013; Park et al., 2011; Petrof et al., 2013; Rakoff-Nahoum et al., 2014; Trosvik et al., 2010) and in vivo (e.g., using gnotobiotic animal models) (Faith et al., 2011; Lee et al., 2013; Mahowald et al., 2009; Roesslers et al., 2011), can provide valuable insights into the impact the activity of one species may have on the growth of another. Notably, the complexity of these experimental communities can vary from very few taxa (e.g., Mahowald et al., 2009; Trosvik et al., 2010) to representations of the entire microbiome (e.g., McDonald et al., 2013). Such assays, however, often do not provide any information about the mechanisms that are at play and may not offer a principled understanding of the processes underlying specific microbe-microbe or microbe-host interactions, particularly when investigating complex communities. Furthermore, since these approaches tend to be labor intensive and costly, they cannot be easily applied to an arbitrarily wide array of distinct communities. Similarly, analyzing the co-occurrence of species across samples (Faust et al., 2012) provides crucial clues into the presence of non-neutral structuring forces, but it may fail to elucidate underlying mechanisms of interaction.

Below, we therefore discuss an alternative, modeling-based approach for studying species interaction. Importantly, we focus mainly on genome-scale metabolic modeling and on studies aiming specifically to provide a mechanistic understanding of such interactions at various scales (Levy and Borenstein, 2014). Other more phenomenological modeling frameworks have been also introduced to quantify, for example, the strength of interactions or to predict microbiome dynamics (e.g., Marino et al., 2014; Stein et al., 2013), yet such models commonly ignore underlying mechanisms of interaction. Genome-scale metabolic models, by contrast, have been instrumental in mapping genotype to phenotype and in elucidating mechanisms of microbial behavior at the single-species level (Borenstein et al., 2008; Reed and Palsson, 2003), and developing methods to extend such frameworks and to model multispecies systems (such as the human microbiome) is therefore a promising route toward a more comprehensive understanding of species interactions (Borenstein, 2012). Multispecies metabolic models have the potential not only to infer unknown modes of interaction but also to provide a detailed account of the underlying metabolic machinery that contributes to such interactions. In the context of the human microbiome, such models are also critical to the development of targeted intervention strategies and the cogent

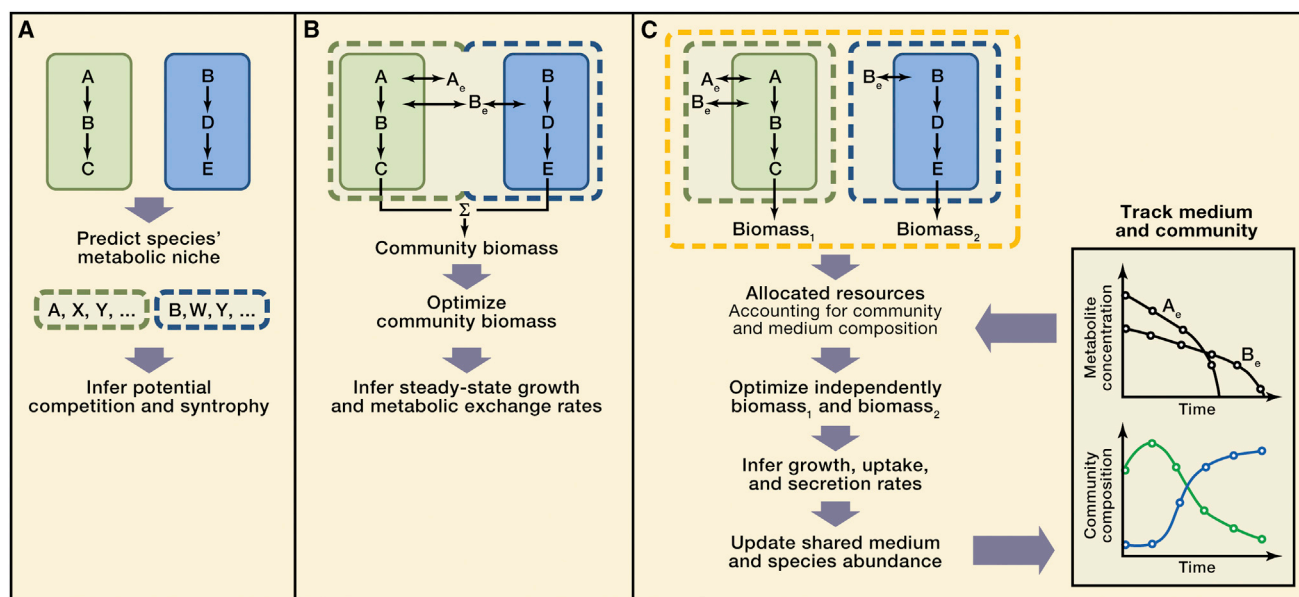


Figure 2. Alternative Multispecies Modeling Frameworks

(A) Simple network-based models can be used to predict the metabolic niche of each species (e.g., using the algorithm introduced in Borenstein et al., 2008). The potential for competition and syntrophy between a pair of species can be inferred by comparing their predicted niches (Levy and Borenstein, 2013).

(B) A common compartmentalization scheme in multispecies constraint-based models includes a separate compartment for each species, a shared medium compartment, and explicit shuttle reactions. Community objective is often defined as a weighted sum of the species' biomass (see, for example, Stoltyar et al., 2007).

(C) A dynamics-based multispecies model, as introduced, for example, in Chiu et al., 2014. The growth of each species is independently optimized according to nutrient availability and allocated resources. This optimization step is used to infer the growth rate of each species, as well as uptake and secretion rates. These are used to update the composition of the shared medium and of the community. By iterating this process, community temporal dynamics can be tracked.

design of synthetic microbiota (Greenblum et al., 2013). Previous attempts at synthetic microbiome design utilized either random combinations of or relatively minor modification to existing genomes (Faith et al., 2014; Kotula et al., 2014; Petrof et al., 2013), and in turn, the internal operation of these systems is often not well understood.

Selecting a Modeling Framework

Over the past few decades, a plethora of metabolic modeling frameworks have been introduced. These frameworks vary greatly in their scale and resolution, in the assumptions underlying the models, and in the information required to reconstruct them. Selection of an optimal modeling strategy is therefore critical and should clearly depend on the research objective and on the nature and scope of available data. In many cases, framework selection may entail a tradeoff between various modeling goals. For example, a simple modeling framework will often offer limited predictive power but can be easily applied to large communities and can utilize a wide variety of data. On the other hand, a more sophisticated framework may offer high-resolution predictions but may only be applicable on a smaller scale or to simpler communities. A modeling framework can also be chosen according to the specific questions to be addressed and to the context of the study. For example, to address questions concerning community metabolism, models may be reconstructed at the metagenome scale (Greenblum et al., 2012), whereas genome-scale models may be used to describe metabolic exchanges between community members or the specific contribution of each member to the community at large. Below, we describe recent advances

in modeling metabolic interactions and discuss considerations of complexity and scale.

Network-Based Models of Species Interaction

One of the simplest yet most powerful approaches for modeling microbial metabolism employs a naive, network-based model to represent the set of biochemical reactions carried out by a given species and focuses on studying the connectivity and topology of such networks as a way to obtain insights into the species' metabolism and ecology (Borenstein et al., 2008; Jeong et al., 2000; Kreimer et al., 2008; Levy and Borenstein, 2012; Stelling et al., 2002; Wunderlich and Mirny, 2006). In such network-based models, parameters such as enzyme kinetics, reaction fluxes, and stoichiometry are often disregarded in favor of a simpler, connectivity-focused representation. While these simplifications potentially reduce the predictive power of the model, network-based models are easy to reconstruct, require minimal information, and can therefore be applied on a very large scale—a critical feature for modeling complex microbiome systems.

Recently, several studies have introduced preliminary attempts to expand such network-based frameworks, moving beyond models of a single species and aiming to model multispecies microbial communities and to obtain insights into their behavior and assembly. Some of these studies, for example, developed methods for integrating several genome-scale metabolic networks and for inferring cross-species metabolic interactions (Figure 2A). This approach has been used, for example, to study host-parasite interactions (Borenstein and Feldman, 2009), bacterial ecological strategies (Freilich et al., 2009), or the global organization of bacterial co-occurrence interactions

(Freilich et al., 2010). Focusing specifically on the human gut microbiome, a recent study used a similar approach to reconstruct genome-scale metabolic network models of >150 gut-dwelling species and introduced a graph theory-based method to predict potential metabolic competition and syntrophy between each pair of species (Levy and Borenstein, 2013). Comparing these predicted interactions with the tendency of species to co-occur in the human gut microbiome (as measured through metagenomic sequencing), this study was able to reveal organizational forces that may govern the assembly of the gut microbiome. Specifically, it was shown that species tend to co-occur with their strongest competitors, suggesting that habitat filtering is a major determinant of community assembly. Importantly, by analyzing the metagenome through the lens of genome-scale metabolic models, this study was able to address questions that metagenomic-based studies cannot. Similar models that directly link the network topologies of interacting species can further identify specific metabolic exchanges between microbial species or between such species and the host (Cottret et al., 2008, 2010).

An additional benefit of this simple, network-based representation of metabolism is that it can be used to model metabolic processes at many different scales, including the scale of the microbiome as a whole. Indeed, network-based models have been applied successfully to a wide range of meta-omic analyses, revealing salient characteristics of the human microbiome. These metagenome-scale models pool all the metabolic reactions that can be catalyzed by the microbiome with no regard for organism boundaries. For example, in one of the first studies to introduce this metagenomic-systems biology framework, Greenblum et al. (2012) projected enzyme abundances from human gut microbiome metagenomic data onto a metagenome-scale metabolic network, demonstrating that microbiome enzymes associated with obesity and with inflammatory bowel disease tend to be located at the periphery of the network. These enzymes represent “contact points” between the community and the host and conceivably would have more influence on or be more influenced by the state of the host. Applying this framework to other meta-omic data could similarly provide insight not available without metabolic modeling. One study, for example, combined network topology with meta-metabolomics to identify modules differentially abundant between pre- and post-small bowel transplant communities, providing a more comprehensive picture of how the human gut community responds to major ecological changes (Hartman et al., 2009). Other studies used meta-transcriptome derived networks to identify pathways not previously associated with periodontal disease (Jorth et al., 2014) or alternative pathways to biomass production (Xiong et al., 2012).

Constraint-Based Models of Species Interaction

A fundamentally different and complementary approach for modeling metabolic interactions between microbial species utilizes the well-established framework of constraint-based modeling (Reed and Palsson, 2003). Such models represent metabolic stoichiometry and known bounds on metabolic fluxes as a set of mathematical constraints and identify a distribution of fluxes that meets the various constraints and that optimizes some predefined objective (Price et al., 2003). Flux balance analysis (FBA), for example, aims to infer the flux through each reac-

tion by optimizing biomass production, ultimately predicting various organismal phenotypes such as growth rate and metabolite uptake and secretion. Often, constraint-based models are thoroughly curated and rigorously validated, thereby sacrificing broad applicability in favor of predictive and descriptive power. A detailed description of the theoretical basis and mathematical formulation of FBA can be found in Orth et al. (2010).

While such constraint-based models have proved extremely successful in predicting the behavior of individual species (Edwards et al., 2001), several crucial elements in their formulation must be extended before they can be applied to model multispecies systems. One such element concerns the compartmentalization of the various reactions included in the model (Taffs et al., 2009). In the first multispecies FBA model of microbial metabolism, which aimed to study the interaction between sulfate-reducing bacteria and methanogenic archaea (commonly found in the cow rumen), the stoichiometry matrix was expanded to represent each species as a separate compartment (Stolyar et al., 2007). Metabolic exchange between the two species was then represented by external shuttle reactions between these compartments through a third compartment representing a shared environment (Figure 2B). This compartmentalization approach became standard and was later used in several other multispecies FBA models (e.g., Freilich et al., 2011; Klitgord and Segrè, 2010; Wintermute and Silver, 2010). One such study has utilized a flux balance approach to predict metabolic interaction among >100 species, demonstrating a close interplay between ecological patterns and the potential for species to compete or cooperate (Freilich et al., 2011). This study further demonstrated that cooperative interactions tend to be unidirectional but that species often form cooperative loops, benefiting all species involved.

An additional modeling element that can greatly influence the applicability and interpretation of an FBA model is the choice of objective function. In the first multispecies model described above, the community objective was defined as a weighted sum of the species' biomass, as determined from empirically measured abundance ratios. However, since growth-rate ratios are typically unknown, more generally applicable solutions have been suggested. The OptCom framework (Zomorodi and Maranas, 2012) utilizes a multilevel objective function, wherein individual species growth represents an inner objective and total community growth represents an outer objective. A global solution can then be found via bilinear optimization. A carefully defined objective function can also facilitate the application of FBA directly to metagenomic data. For example, a recent study of the interaction between three gut dwelling species used a multispecies FBA model coupled with two distinct objective functions, each applied to address a different prediction task (Shoaie et al., 2013). First, metabolic secretion was predicted given a defined dietary input and was solved by constraining microbial abundances while minimizing substrate uptake rates. Subsequently, species abundances were also predicted by constraining uptake rates and optimizing total community growth. Notably, fatty acid secretion and metabolic reprogramming predicted by the model were in accord with experimentally measured values (Mahowald et al., 2009). Another solution was introduced in the first constraint-based model of a gut microbe interacting with its eukaryotic host (Heinken et al., 2013). In this

framework, the growth of one organism was constrained while that of its partner was optimized, describing the trade-off between host and microbe optimal growth. Notably, this model was able to demonstrate mutualistic growth in an idealized host-microbiome system, as well as rescue of a lethal host genotype by a symbiont. Although in this study a generic mouse model (with extension for intestinal transport and absorption) was used for the host, well-curated human metabolism models (Duarte et al., 2007) (as well as tissue-specific models; Jerby et al., 2010; Wang et al., 2012) have been introduced and can be similarly integrated into a more accurate host-microbiome model.

The success of the modeling approaches described above in recovering observed patterns of microbial interaction highlights the potential of multispecies constraint-based models, but it also warrants a discussion of the limitations of these frameworks and of potential solutions. First, it is unclear how these frameworks scale with community complexity and how they may be used to model more complex interactions. Multispecies constraint-based models are still in their early days, and efforts are mainly focused on developing approaches for modeling very simple communities. Second, naively defined objectives have the potential to produce biologically implausible predictions. Specifically, the commonly used objective function that aims to maximize total community growth (e.g., Shoaie et al., 2013; Stolyar et al., 2007) inherently assumes altruistic cooperation between community members and may therefore predict that one species neglects its own growth to facilitate the faster growth of another.

Introducing temporal dynamics and expanding single-species dynamic FBA models (e.g., Collins et al., 2012) to account for multiple species with a shared environment may provide a viable alternative (Figure 2C). In such dynamics-based frameworks, the growth of each species is optimized independently of its partners' growth on a short time scale (as determined by nutrient availability), and the shared environment is iteratively updated according to predicted species' growth, uptake, and secretion rates (Chiu et al., 2014; Tzamali et al., 2011; Zhuang et al., 2011). Competitive effects and metabolic interactions are therefore mediated through the environment as a natural byproduct of niche construction, rather than being explicitly formulated in the model. Importantly, in this way, the need to optimize a more complex and potentially artificial objective function at the community scale is circumvented. Instead, community dynamics over a long timescale are revealed through integration of discrete time steps. Using this approach, a recent study integrated dynamic FBA with flux variability analysis to model metabolic interaction across hundreds of two-species consortia and to study the emergence of metabolic capacity in such simple communities (Chiu et al., 2014). Indeed, emergent biosynthetic capacity, wherein a multispecies community secretes into the environment metabolic products that no constituent species secretes when grown in isolation, was found to be prevalent. Using this modeling framework, it was also shown that emergent biosynthetic capacity commonly occurs in two distinct phases of community growth and that it is most probable when community members have moderately similar sets of metabolic capabilities (Chiu et al., 2014).

Integrating Metabolic Modeling with Other Modeling Approaches

Metabolic models, of course, are not the only modeling frameworks capable of generating hypotheses or predictions of microbiome behavior, and other frameworks, focusing on ecological dynamics or on spatial organization, have been recently introduced. Such alternative modeling frameworks are often complementary and could be coupled in exciting ways. Stein et al. (2013), for example, introduced a generalized Lotka-Volterra model of species growth rates, interactions, and antibiotic susceptibility capable of predicting community dynamics over a large timescale, as well as response to antibiotic perturbation (and see also Marino et al., 2014). Notably, the parameters of this model were learned directly from metagenomic data without utilizing any prior knowledge of species physiology. Similarly, Trosvik et al. (2010) applied a Generalized Additive Model to time-series data representing growth of a model gut community to quantify the influence of intrinsic microbe-microbe interactions. Metabolic models could complement such efforts both "upstream" by informing the search for optimal parameters and "downstream" by offering a mechanistic interpretation to phenomenological model predictions. Agent-based models have been proposed to account for spatial resolution in studying species interaction (Kreft et al., 2013; Schluter and Foster, 2012) and have been successfully applied to study small cooperative communities (Momeni et al., 2013a, 2013b). In such agent-based models, the microbe's internal complexity is mostly stripped down to allow implementation and tractability, and the rule set that determines the behavior of each agent is often somewhat arbitrary. Metabolic models can offer an attractive solution and could be used, for example, to determine the general behavior of a group of agents at specific time steps, leading to a true multiscale model. A simpler alternative approach for integrating metabolic modeling and spatial resolution has recently been introduced, where a constraint-based metabolic model was used to predict the behavior of various microbial species over a short time scale and a lattice-based environment and classical diffusion dynamics were used to determine how metabolites are exchanged between adjacent microhabitats (Harcombe et al., 2014).

Concluding Remarks

Our ability to generate computational models of complex biological systems is rapidly improving. Yet, even as we are beginning to address the challenge of modeling whole cells (Karr et al., 2012), we are still a ways from generating equally comprehensive models of whole communities. Host-associated communities pose additional challenges, as host phenotypic response and its impact on the community further complicate any modeling framework and prohibit many typical simplifying assumptions (Heinken et al., 2013; Thiele et al., 2013). The influences of gene regulation and genotypic variation are also currently largely ignored in metabolic models, but they must be taken into account to achieve the desired level of comprehensiveness or for applications to personalized medicine. Similarly, microbe-microbe signaling and antibiotic production are not within the scope of metabolic models, but they greatly impact growth. Finally, our ability to identify gene families has rapidly outpaced our ability to functionally characterize them: by some estimates,

as many as 75% of identified genes lack a functional annotation (Qin et al., 2010), yet enzymatic characterization is crucial to inclusion in metabolic models. Analogous to the aforementioned microbial “phylogenetic dark matter”, these uncharacterized genes represent a “functional dark matter”; it is potentially responsible for the most interesting and complex capacities of the microbial world, yet its precise function and the way such functions are carried out remain a mystery. Ironically, in successfully mapping the phylogenetic dark matter, we accelerate the discovery of uncharacterized gene families and of such functional dark matter, revealing how little we know of microbial metabolism at large. As advanced as high-throughput genomic technologies may be, meticulous, low-throughput biochemical assays still represent the ultimate solution to this problem, highlighting the importance of constant feedback between characterizing the elements of the systems and the system as a whole.

AUTHOR CONTRIBUTIONS

O.M., R.L., and E.B. wrote the paper.

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