

Using Data and Analytics to Unlock the Microbiome Impact on Human Health

世良 実穂

Clarivate Analytics

シニアコンサルタント

Cortellis

Powering Life Sciences Innovation



Clarivate
Analytics



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Director, Informatics, Discovery and Translational Services

Who is Clarivate?

Metabase

- Largest manually curated database of protein, RNA, drug and metabolite interactions;
- Available for human, mouse and rat;
- Comes with a versatile toolkit of methods for network analysis

Metacore

- User interface to Metabase with integrated pathway analysis workflows for diverse OMICs datasets;
- More than 1600 richly annotated pathway maps for results visualisation

Integrity

- Compound-target database containing over 450 000 compounds with biological activity;
- Supported by data on pharmacology, PK, experimental models, patents, clinical studies, etc.

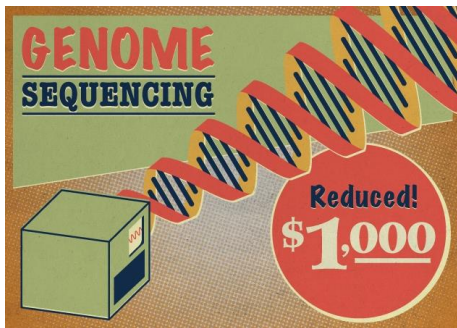
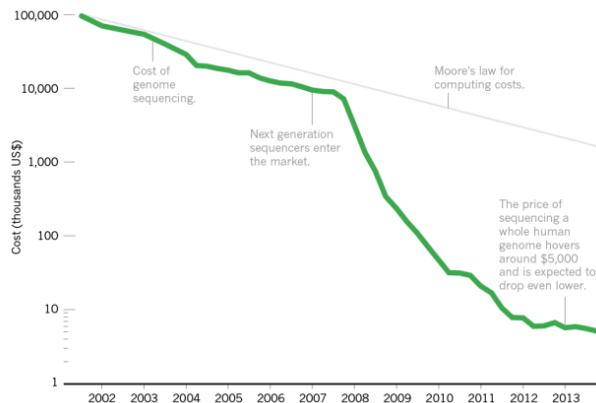
Cortellis

- Suite of intelligence solution for late stages of drug development;
- Provides intelligence in Drug Pipeline, Clinical Trial and Regulatory areas

Why Microbiome

Falling fast

In the first few years after the end of the Human Genome Project, the cost of genome sequencing roughly followed Moore's law, which predicts exponential declines in computing costs. After 2007, sequencing costs dropped precipitously.



The Importance of the **MICROBIOME** by the Numbers



90%

Up to 90% of all disease can be traced in some way back to the gut and health of the microbiome

10-100 trillion

Number of symbiotic microbial cells harbored by each person, primarily bacteria in the gut, that make up the human microbiota

>10,000

Number of different microbe species researchers have identified living in the human body

10X

There are 10 times as many outside organisms as there are human cells in the human body

100

100 to 1

The genes in our microbiome outnumber the genes in our genome by about 100 to 1

3.3 million

Number of non-redundant genes in the human gut microbiome

22,000

Approximate number genes in the human gene catalog



99.9%



Percentage individual humans are identical to one another in terms of host genome



Percentage individual humans are different from one another in terms of the microbiome



80-90%





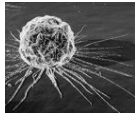
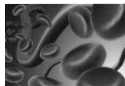


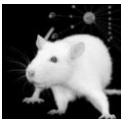
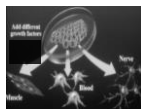






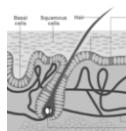
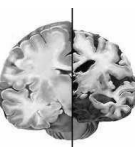

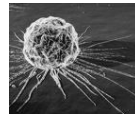
Clarivate Analytics' Solutions in the Microbiome Space

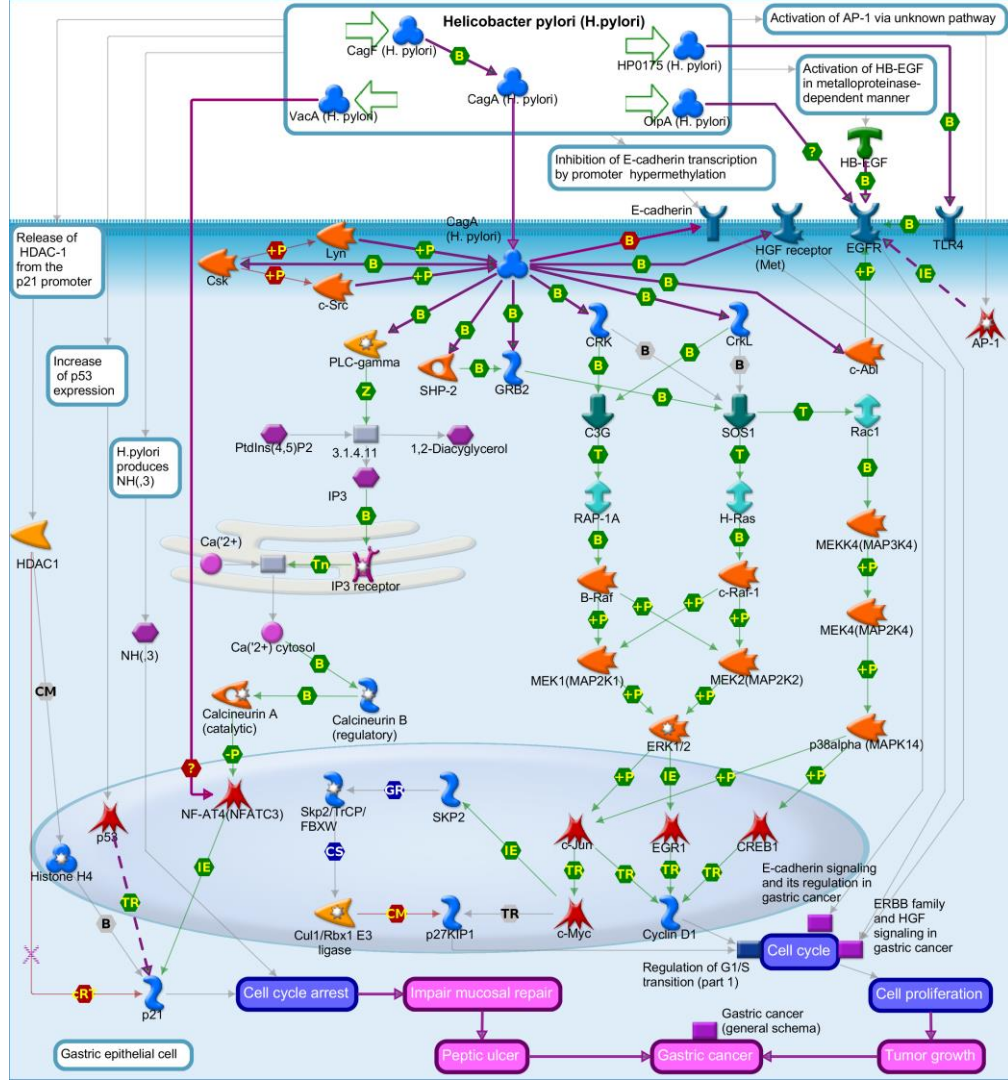
1. Manual curation of microbial pathways and host-microbial interactions from publications
2. Curation and harmonization of public datasets for large-scale meta-analyses
3. Bioinformatics services and custom end-to-end software development

Clarivate Analytics' Solutions in the Microbiome Space

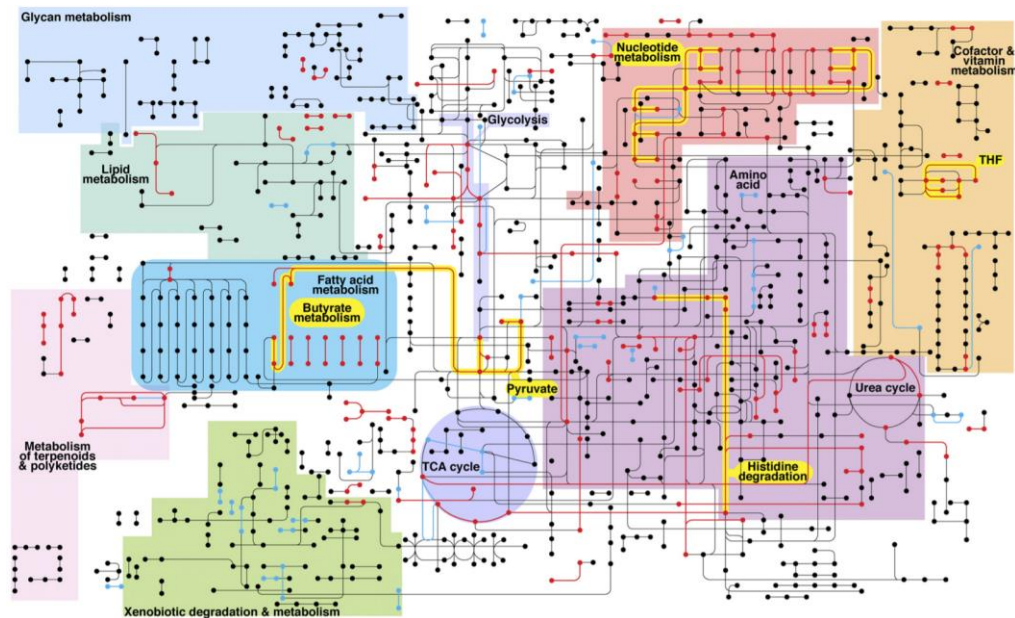
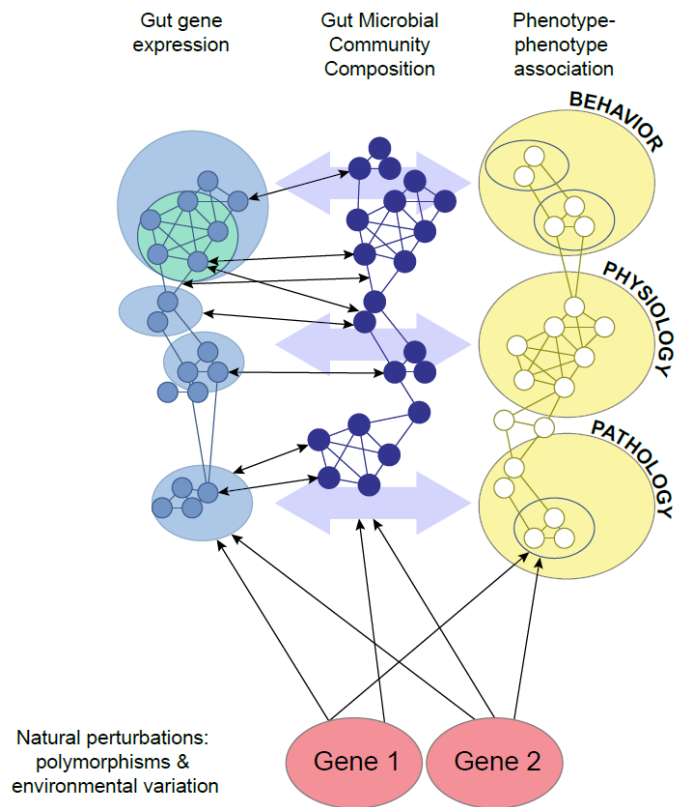
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Pathway Curation – MetaMiner Partnerships

Completed						Coming soon	
<p>Cystic Fibrosis</p>  <p>CFF Foundation</p>	<p>Asthma</p>  <p>AZ, JNJ, Merck</p>	<p>Prostate Cancer</p>  <p>Exclusive Project</p>	<p>Multiple Sclerosis</p>  <p>Vertex, IOP</p>	<p>Oncology</p>  <p>Eli Lilly Millennium J&J Tgen Van Andel Harvard Johns Hopkins CRUK</p>	<p>Hematology</p>  <p>Exclusive Project</p>	<p>Immunology</p>  <p>Celgene, BI</p>	<p>Microbiome</p> 
<p>Toxicology</p>  <p>Elan FDA Vertex</p>	<p>Stem Cells</p>  <p>Astra Zeneca Eli Lilly Novartis Chicago Children's Hospital University of Glasgow University of Sheffield University of Queensland USC</p>	<p>Dry Eye</p>  <p>Exclusive Project</p>	<p>Depression</p>  <p>Vertex, IOP</p>	<p>Diabetes, Obesity, Metabolic Syndrome</p>  <p>Eli Lilly TNO FDA University of Amsterdam</p>	<p>COPD</p>  <p>AZ</p>	<p>Eye Diseases</p>  <p>Novartis</p>	<p>Drug combinations</p> 
		<p>Dermatitis</p>  <p>Unilever</p>	<p>Huntington's</p>  <p>CHDI</p>	<p>Neurofibrom atosis</p>  <p>Children's Tumor Foundation</p>	<p>Immuno Oncology</p>  <p>3 large Pharma 1 small Pharma</p>		



Microbiome-Host Modelling Challenges



Database of Microbial-Host Interactions (DoMI – Article Examples

Protein-protein interactions

Chemistry & Biology Article

Host-Microbe Protein Interactions during Bacterial Infection

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<http://dx.doi.org/10.1016/j.cel.2015.03.015>

SUMMARY

Interspecies protein-protein interactions are essential mediators of infection. While bacterial proteins required for host cell invasion and infection can be identified through bacterial mutant library screens, information about host target proteins and interspecies complex structures has been more difficult to acquire. Using an unbiased chemical crosslinking mass spectrometry approach, we identified interspecies protein-protein interactions in human lung epithelial cells infected with *Acinetobacter baumannii*. These efforts resulted in identification of 3,076 crosslinked peptide pairs and 46 interspecies protein-protein interactions. Most notably, the key *A. baumannii* virulence factor, OmpA, was identified as crosslinked to host proteins involved in desmosomes, specialized structures that mediate host cell-to-cell adhesion. Co-immunoprecipitation and transposon mutant experiments were used to verify these interactions and demonstrate relevance for host cell invasion and acute murine lung infection. These results shed new light on *A. baumannii*-host protein interactions and their structural features, and the presented approach is generally applicable to other systems.

INTRODUCTION

Interspecies protein interactions and the underlying structural interfaces are essential for bacterial infection. The molecular level arms race between hosts and pathogens is carried out on multiple fronts, but predominantly takes place through evolutionary adaptation of protein structural landscapes (Eide et al., 2010; Eide and Maitl, 2009; Duggan et al., 2013; Barber and Eide, 2014; Patel et al., 2013). Bacteria control host resources through evolutionarily optimized bacterial protein structures that bind with high specificity to host protein cognates. Pathogen proteins target diverse host proteins involved in metabolic acquisition (Barber and Eide, 2014), molecular targeting to the cell membrane (Eide and Maitl, 2009), cytoskeletal rearrangement (Cossart and Lacks, 1998), and cell adhesion

complexes (Oude et al., 2010). As an example, iron is necessary for biochemical processes in both bacteria and hosts, and can be sequestered by the verotoxin membrane protein transferrin to defend against bacterial infection (Barber and Eide, 2014; Zamboni et al., 2013). In response, bacteria such as *Neisseria gonorrhoeae* and *Haemophilus influenzae* have evolved transferrin-binding proteins (Tbp) capable of binding and scavenging iron directly from transferrin to overcome sequestration (Gambrell et al., 2007). Barber and Eide (2014) showed that single point mutations in transferrin alter Tbp affinity at the interface of the two proteins and are responsible for establishing the host range of the bacteria and modulating host nutritional immunity. Therefore, knowledge of not only the proteins involved in host-pathogen protein interactions but also the manner of their interaction, i.e. structural insight into interfacial regions, can profoundly advance understanding of bacterial infection and provide insight for the development of new antimicrobial therapies (Barber and Eide, 2014).

Technologies have evolved to allow large-scale protein interaction identification, but relevant information on host-pathogen interspecies interactions and structures is still limited. Two-hybrid (Fink and Song, 1998), affinity purification mass spectrometry (MS) (Bloom et al., 2003) and protein complementation (Frasconi et al., 2003) methods have made the large-scale study of protein-protein interactions (PPI) possible. Although recent years with these techniques have demonstrated the ability to identify PPIs relevant to host-pathogen interactions, including the virus-human protein interactions of HIV (Lipor et al., 2013) and HTM (Shugart et al., 2008), host-pathogen PPIs remain a general challenge to identify. Furthermore, structural details pertaining to host-pathogen protein interactions are exceedingly sparse. Many aspects of host-pathogen interactions are mediated by membrane proteins, as exemplified by the transferrin case above. With roles in signal sensing, secretion, adhesion, and invasion, membrane proteins play pivotal roles in bacterial pathogenesis, yet they often require significant dedicated efforts for interaction studies, are less suitable for many large-scale methods, and are equally challenging for conventional structural characterization (Caporaso et al., 2008).

Alternative technologies have the potential to shed light on interspecies PPIs and further structural interfaces. Chemical crosslinking MS (CL-MS) approaches are beginning to have a greater impact on protein interaction studies (Tang et al., 2003; Hering et al., 2012; Garg et al., 2007; Polosinski and Boeckmann, 2010; Yang et al., 2012; Toit et al., 2013). Because of the fibril

Cell Press

Metabolite-protein interactions

Immunity Article

Activation of Gpr109a, Receptor for Niacin and the Commensal Metabolite Butyrate, Suppresses Colonic Inflammation and Carcinogenesis

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<http://dx.doi.org/10.1016/j.immuni.2013.12.007>

SUMMARY

Commensal gut microflora and dietary fiber protect against colonic inflammation and colon cancer through unknown targets. Butyrate, a bacterial product from fermentation of dietary fiber in the colon, has been implicated in this process. GPR109A (encoded by *Niacr1*) is a receptor for butyrate in the colon. GPR109A is also a receptor for niacin, which is also produced by gut microbiota and suppresses intestinal inflammation. Here we showed that Gpr109a signaling promoted anti-inflammatory properties in colonic macrophages and dendritic cells and enabled them to induce differentiation of Treg cells and IL-10-producing T cells. Moreover, Gpr109a was essential for butyrate-mediated induction of IL-10 in colonic epithelium. Consequently, *Niacr1*^{-/-} mice were susceptible to development of colonic inflammation and colon cancer. Niacin, a pharmacological Gpr109a agonist, suppressed colitis and colon cancer in a Gpr109a-dependent manner. Thus, Gpr109a has an essential role in mediating the beneficial effects of gut microbiota and dietary fiber in colon.

INTRODUCTION

Commensal microbiota in the gut have profound effects on human health (Bischoff et al., 2005; Honda and Littman, 2013). Germ-free and antibiotic-treated mice are more susceptible to dextran sulfate sodium (DSS)-induced colonic inflammation (Mackowski et al., 2009; Takai-Nishimura et al., 2009). Bacteroides fragilis and Clostridium clusters IV and XIVa protect against inflammatory bowel disease (IBD) and colorectal cancer (Kumar et al., 2011; Macmanus et al., 2009). Multiple intestinal neoplasia (MIN, *Apc*^{+/+}) mice carry a germline truncating mutation in one copy of *Apc* and spontaneously develop adenomas throughout the intestinal tract. *Lactobacillus acidophilus* and

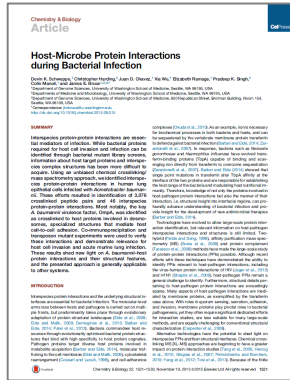
certain gut microbial metabolites such as conjugated linoleic acids decrease intestinal tumorigenesis in *Apc*^{+/+} mice (Davis and Miller, 2009; Uehara et al., 2008). In contrast, depletion of microbiota ameliorates intestinal inflammation and cancer in mouse models of spontaneous colitis (R17^{-/-}, *Rag1*^{-/-}, *Rag2*^{-/-}, or *Apc*^{+/+}) (Kam et al., 2008; Gonsky et al., 2012; Li et al., 2012; Uehara et al., 2009). Bacteroides fragilis toxin (BFT) and Bacteroides vulgatus increases inflammation and colon cancer in *Apc*^{+/+} and R17^{-/-} mice, respectively (Uehara et al., 2009; Wu et al., 2009). Thus, commensal bacteria promote as well as suppress colonic inflammation and colon cancer in a context-dependent manner.

One of the mechanisms by which gut microbiota promote colonic health is through production of the short-chain fatty acids (SCFAs) acetate, propionate, and butyrate by fermentation of dietary fiber. Among SCFAs, butyrate has received most attention for its effects on colonic health (Barber et al., 2008). The functions of butyrate in promoting colonic health range from being energy source for colonocytes to being a key mediator of anti-inflammatory and antitumorigenic effects. Gut microbiota analysis has revealed a significant decrease in the number of butyrate-producing bacteria in colon of patients with ulcerative colitis and colon cancer (Frank et al., 2007; Wang et al., 2013). Colonic ingestion with butyrate suppresses inflammation during ulcerative colitis (Furuta et al., 2008).

IL-10 deficiency leads to spontaneous colitis (Huber et al., 2001; Issa et al., 2000; Rubtsov et al., 2008). Polymorphisms in the genes that encode IL-10 or IL-10 receptor are linked to increased incidence of ulcerative colitis and inflammatory bowel disease (Frank et al., 2008; Glocker et al., 2009). Human monocyte-derived dendritic cells (DCs), when matured in the presence of butyrate, have increased expression of IL-10 and decreased production of IL-6 (Mullard et al., 2002; Wang et al., 2008). IL-18 plays an essential role in suppression of colonic inflammation and inflammation-associated cancers (Chen et al., 2011; Duggal-Chickole et al., 2010; Elavar et al., 2011; Salcedo et al., 2010; Zaki et al., 2013). Moreover, an IL-18 gene promoter polymorphism leading to decreased expression is found at higher frequency in patients with ulcerative colitis (Kalogirou et al.,



Database of Microbial-Host Interactions (DoMI) – Literature Annotation Data Elements



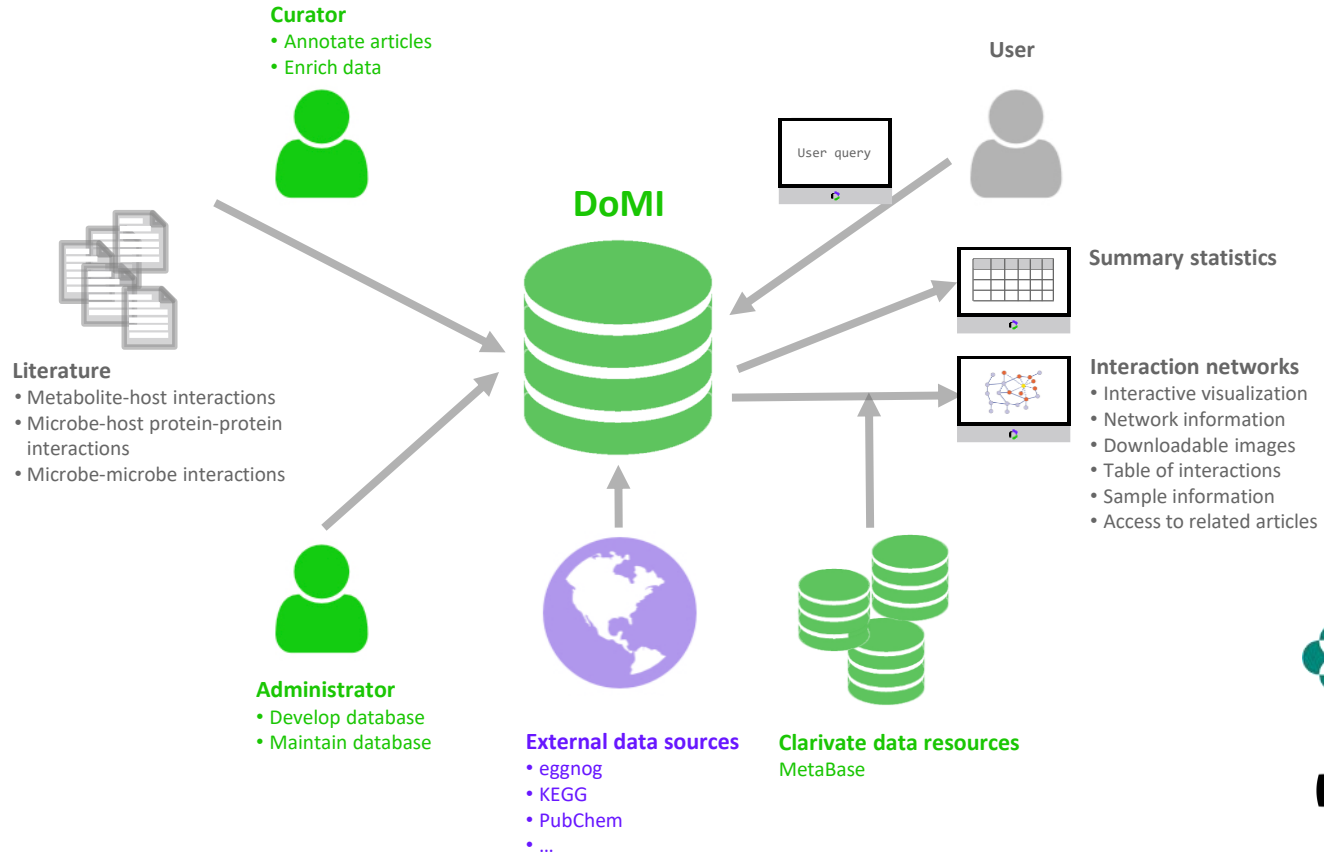
Fields for annotation (protein-protein interactions):

- PubMed ID
- Protein names & IDs
- Gene names & IDs
- Organisms, including species and strain
- Interaction detection method
- Host system (tissue/cell line)
- Type/mechanism of interaction (e.g. binding, transcription regulation, influence on expression)
- Effect of interaction (i.e. activation, inhibition, unknown)
- Confidence (interaction reliability based on interaction types and detection methods)

- Controlled vocabularies
- IDs
- Metadata

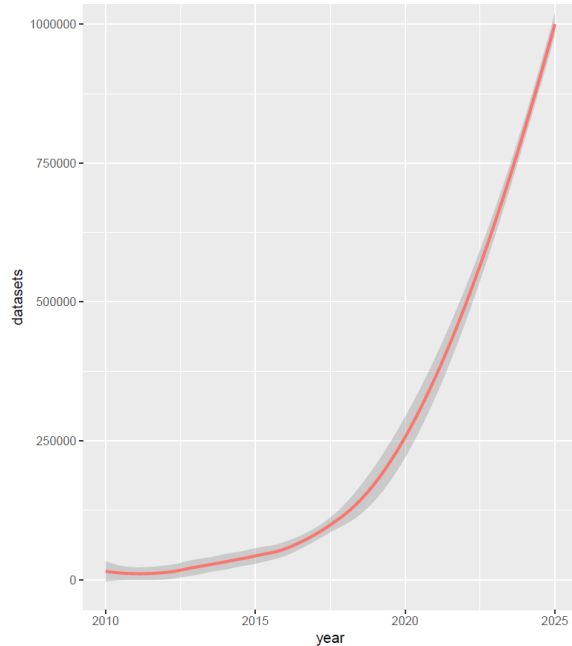


Database of Microbial-Host Interactions (DoMI)



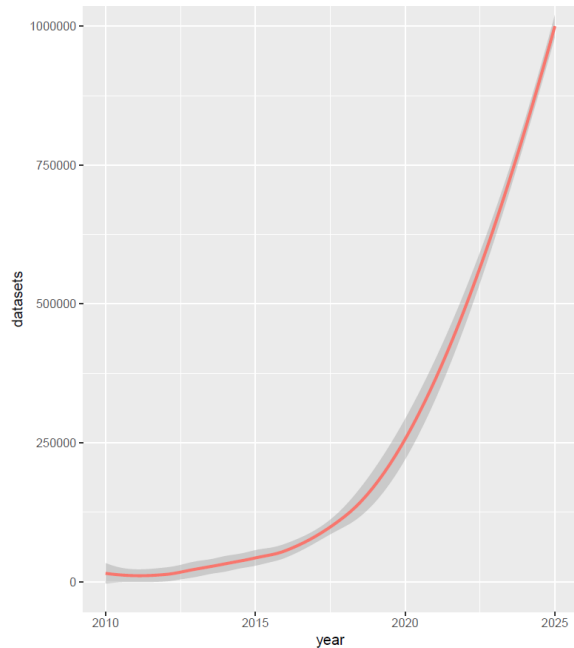
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1. Manual curation of microbial pathways and host-microbial interactions from publications
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What's the Problem with This?

1. Lack of consistent terminology
2. Scarce meta-data: critical information is often only contained in paper full texts



Programmatic text mining

Study level



Biomes diversity
• Human
• Stool



Including large-scale projects



• Disease
• Healthy



Major public data repositories



Number of samples



• Center name
• Platform
• Number of runs



Data size



• Submission date
• Analysis status



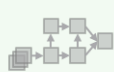
Publications
• Title
• Authors
• PubMed ID



Study design
• Cross-sectional
• Longitudinal



Experimental methods
• Collection
• Extraction



Bioinformatics analysis workflows



Host/microbiome additional data
• Transcriptomics
• Proteomics
• Metabolomics

Sample level



Sample identification
• Name
• Sample ID
• Subject ID
• Project name



Traceability
• Collection date
• Geographic location
• Body site



Host
• Age
• Gender
• Ethnicity
• Disease



Sequencing
• Library source
• Platform
• Single/paired end
• Read length
• Number of reads



Biome
• Organism
• Material
• Features



Sequence of focus:
• Amplicon variable region



Genotype information (yes/no)



Sample source
• Stool
• Intestinal biopsy
• Intestine region

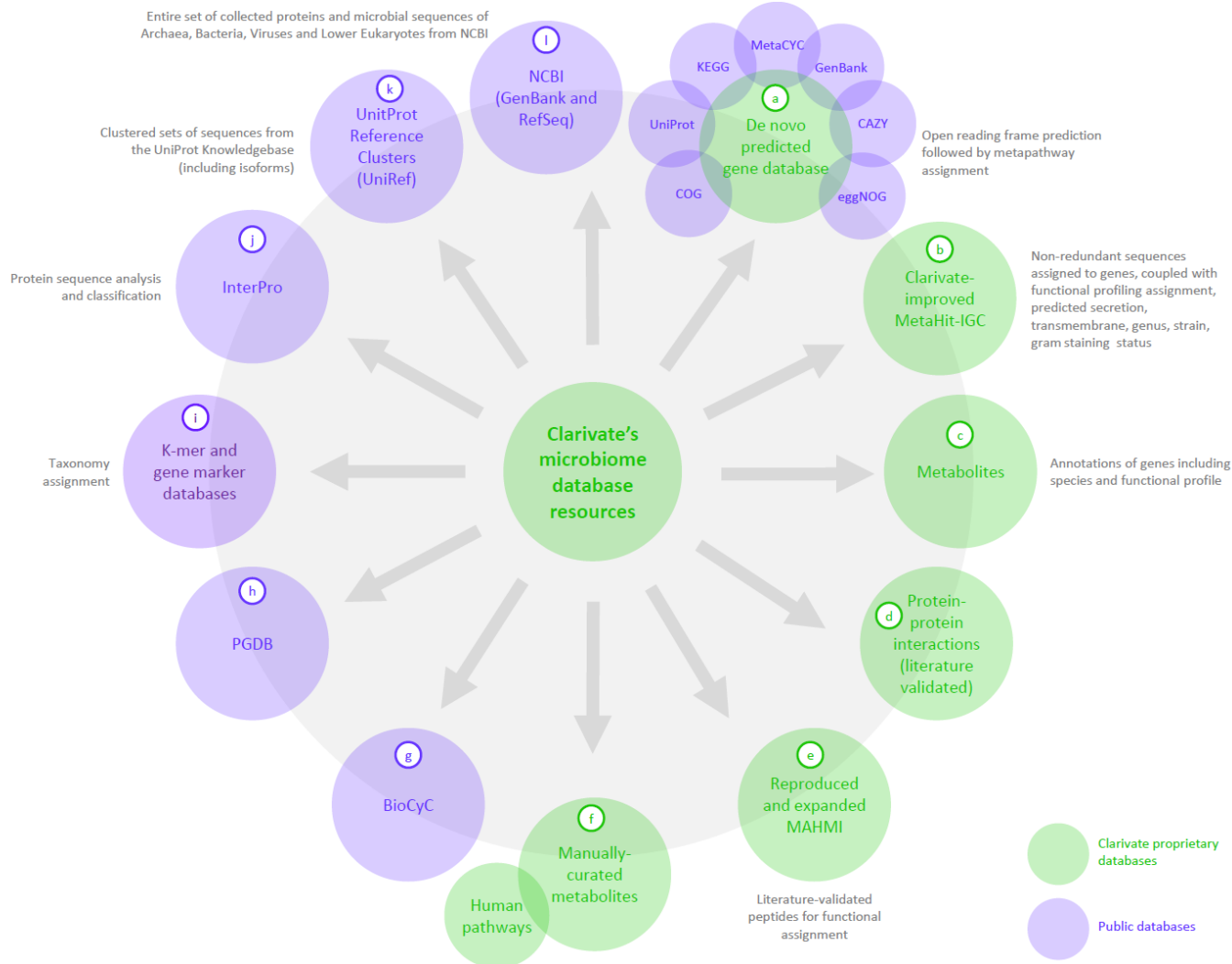


Disease details
• Disease subtypes
• Active/inactive, etc

Manual literature curation

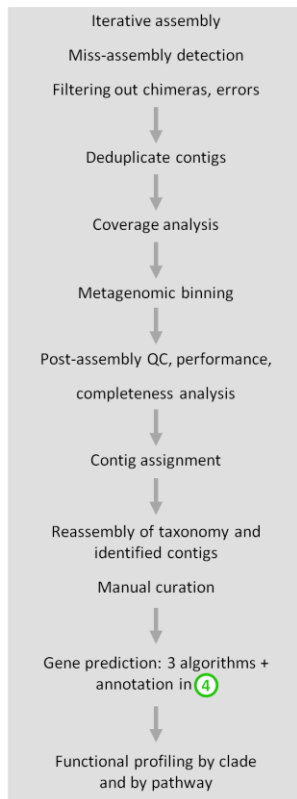
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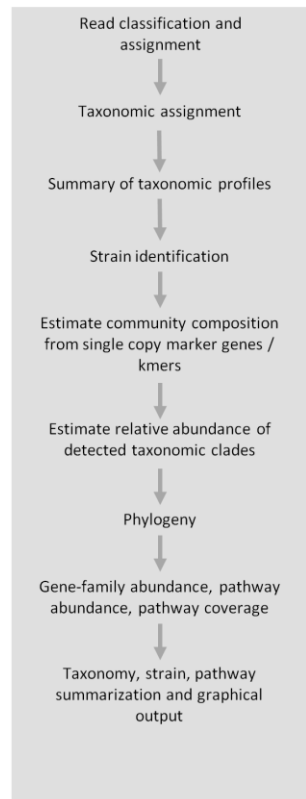
1 Assembly of metagenomes

- a) Quality control and filtering
- b) Metagenome reconstruction
- c) Gene count, prediction
- d) Meta-pathway prediction



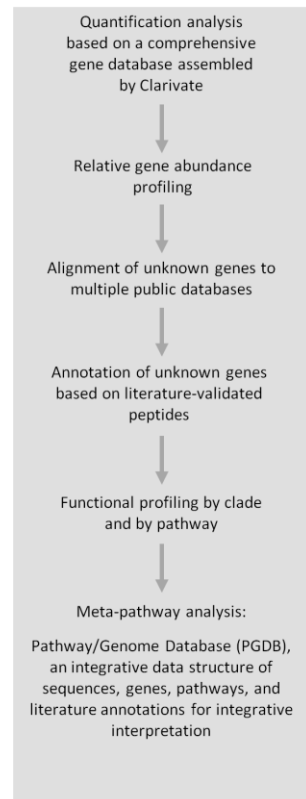
2 Community summarization

- a) Gene marker analysis
- b) Kmer-based analysis
- c) Strain identification
- d) Functional profiling



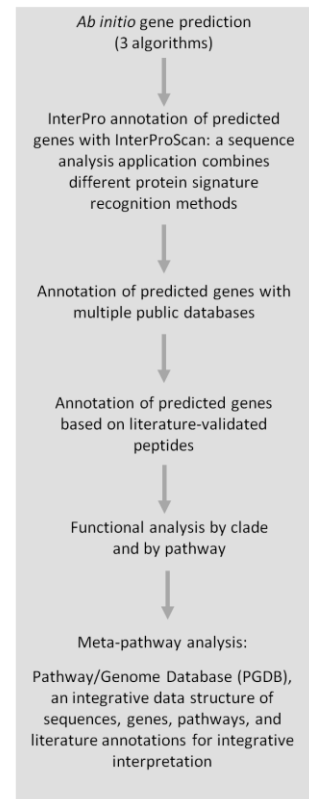
3 Gene quantification

- a) Gene quantification
- b) Functional profiling
- c) Gene count, prediction
- d) Meta-pathway prediction



4 De novo gene identification

- a) Gene *de novo* prediction
- b) Protein signature recognition
- c) Functional assignment
- d) Meta-pathway prediction



Cases of Bioinformatics Projects

- Target molecules identification
- Target disease prioritization
- Reconstruction of drug MoA
- Drug repositioning
- Patient stratification
- Concomitant drug identification
- Cell type prediction
- Microbiome

Your Objectives

Define and Design

Implementation



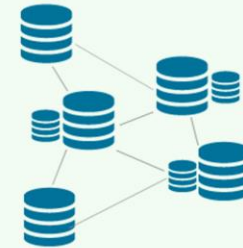
TypeScript



ORACLE
DATABASE



Database Development



Data Integration

